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Distribution System Planning Considering Stochastic EV Penetration and V2G Behavior

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***Abstract*— The increasing integration of electric vehicles (EVs) is adding higher future potentials for the smart grid because residual energy stored in EV batteries can be discharged to support the grid when needed. However, the stochasticity of EV user behaviors poses challenges to the regulators of distribution systems. How regulators decide upon a control strategy for the vehicle to grid (V2G) and how EV users respond to the strategy will significantly influence the variation of load profiles in the planning horizon. In this paper, a comprehensive cost analysis is performed to obtain the optimal planning scheme considering the variation in EV penetration, charging preference, and customer damage cost (CDC). The economics and stability of the planned distribution system are assessed with real-world travel records and cost statistics to quantitatively show the effectiveness of the optimization algorithm and the importance of user behavior concern.**

***Index Terms*—Distribution system planning, vehicle to grid, stochastic user behavior, customer damage cost.**

Nomenclature

CDC	Customer damage cost
DG	Distributed generation
EPC	The engineering, procurement and construction
EV	Electric vehicle
H	Residential areas
SOC	State of charge
V2G	Vehicle to grid
N	Total number of public charging places.
i	Index of EVs
λ	Index of planning years
$T_{c,n}^{i}$	Trip end time of EV i at place n
S_{n}^{i}	Trip start time of EV i at place n
$l_{n,n+1}^{i}$	Travel distance between place n and n+1 of EV i
B_c	Total capacity of EV batteries
E_{n}^{i}	Possible charging demand of EV i at place n
ω	Energy consumption per km
D_{H}^{i}	Charging duration of EV i at H
P_c, κ_c	Charging power and efficiency
ξ^i	Customer damage cost (CDC) of EV i
μ_c, δ_c	The mean and standard deviation of CDC
γ_λ	Compensation ratio at year λ
T_{gc}, D_{gc}	Control start time and lasting period
T_{c}^{i}, D_{c}^{i}	Charging start time and duration of EV i
$e_{residual}$	The residual battery energy at time T_{gc}
P_d, κ_d	Discharging power and efficiency
e_{c}^{i}	Energy already charged before T_{gc} of EV i
e_{b}^{i}	Energy discharged of EV i
e_{p}^{i}	Postponed original charging demand of EV i
t^*	Reference recharging time.
T_{r}^{i}, D_{r}^{i}	Recharging start time and duration of EV i
$P_{t}^{c,EV}$	Total charging power at time t
$P_{t}^{d,EV}$	Total discharging power at time t
Y	Number of years for entire planning horizon
f^{oper}	Total operation cost
f^{cc}	Total customer compensation cost
f^{inv}	Total investment cost
d^{annual}	Number of days in one year
ρ_{t}^{da}	Day-ahead electricity price at time t
$\rho^{CO}2$	Fixed carbon tax rate
ρ^{NL}	Unit line loss rate
$P_{t,\lambda}^{s}$	Total power demand at the substation
$P_{t,\lambda}^{loss}$	Total system line loss power
π^{LL}, π^{LS}	Annuity transform parameter for feeders and substations
ρ^{EL}, ρ^{ES}	Fixed cost for feeders and substations
ρ^{CL}, ρ^{CS}	Capital cost for feeders and substations
q_λ	the number of total EV users at year λ.
$P_{xy,cap}^{l}$	Adequate capacity of feeder
$P_{x,cap}^{s}$	Adequate capacity of substation
Ω^l	Set of feeders
Ω^s	Set of substations
Ω^x	Set of system nodes
Ω^t	Set of time intervals in a day
$P_{x,t}^{c,EV}$	EV charging power at node x, time t
$P_{x,t}^{d,EV}$	EV discharging power at node x, time t
$P_{x,t}^{base}$	Base power load at node x, time t
$P_{x,t}^{s}$, $Q_{x,t}^{s}$	Active and reactive power generation
$P_{x,t}^{base}$, $Q_{x,t}^{base}$	Active and reactive base power load
$U_{x,t}$	Nodal voltage
G_{xy}, B_{xy}	Real part and imaginary part of nodal admittance matrix

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I. Introduction

POPULARIZING electric vehicles (EVs) can effectively reduce greenhouse gas emissions and dependence on fossil fuels. However, existing studies illustrate that the increasing integration of EVs with stochastic behavior and improper energy management may increase operational pressure on the existing power grid [1]-[4].

There are largely two ways for easing the impact of EV penetration on power systems. One is to control user charging behaviors directly for better peak shaving. The two-stage co-ordination strategy considered in [5] optimizes the charging power of the aggregators at the upper level and reschedules individual EVs accordingly at the lower level. Synergistic control of EV charging and other distributed generation (DG) systems are analyzed in [6]-[8]. Vehicle to grid (V2G) technology can fully utilize EV battery potentials that discharge during busy hours to support the grid and recharge at valley hours [9]-[12]. However, they seldom consider the willingness of EV users or their temporal availability for obeying controls from the grid. The price lever is introduced in [12]-[14] to guide charging behaviors, but different user perspectives with respect to the amount of incentives are not considered. A cooperative game between grid regulators and customers is proposed in [15]-[16] in which the decrement of the total cost is allocated to each participating player. The game is based on the hypothesis that users are fully responsive, which may not be realistic for the V2G behavior.

Another feasible method is to upgrade power system infrastructure ahead of the increasing EV charging demand anticipated over the long-term planning horizon. The distribution system planning proposed in [17]-[29] aims to reduce the infrastructure investment cost and system operation cost. Constructing DGs that provide wind and solar energy is suggested as an option in [18]-[25], but the power from DGs is intermittent and cannot guarantee timely support during busy hours. An incentive-based planning is proposed in [24] that grid investors and DG investors collaborate for mutual benefits. The extra cost of automation equipment in distribution system expansion is taken into account in [26]. Optimal siting and capacity of EV charging stations within metropolitan areas are investigated in [27]-[29]. However, the stochasticity of EV user behavior is underestimated that no incentive is provided for mutual benefits of grid investors and EV users.

Considering stochastic V2G behavior in residential areas, probabilistic evaluation of a power system can recognize not only the severity of a state and its impact on system operation but also the probability of its occurrence. In the long-term distribution planning, a proper combination of both severity and occurrence probability creates indices that better represent system reliability and risk. It is common that more investment brings a higher reliability level but it's hard to quantify the correlation. [23] considers the reliability penalty as a preset percentage of the cost of the energy supplied by substations while fuzzy optimization technique is used in [25] to handle these two contradicting objectives, namely, decreasing cost and improving reliability. However, the quantified correlation obtained in [23] and [25] is based on assumed data.

Table I
COMPARISON OF DISTRIBUTION PLANNING MODELS

	With DG	With EV	Reliability concern	Mutual benefits
[17-20], [26]	✔	✖	✖	✖
[21-22]	✔	✖	✖	✖
[23], [25]	✔	✖	✔	✖
[24]	✔	✖	✖	✔
[27-29]	✖	✔	✖	✖
Proposed model	✖	✔	✔	✔

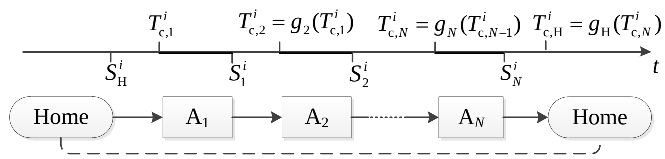

Fig. 1 Illustration of travel route modeling

Distribution system planning expands existing grid assets according to future load growth. The appropriate incentive control strategy may attract V2G adoption for peak mitigation and facilitate an overall cost reduction of system planning. Single cost-related functions which consider customer interruption cost or infrastructure upgrade cost independently, are used in [17]-[23] and [25]-[29]. However, a trade-off always exists among grid reliability, facility reinforcement cost, and incentive control cost. A single objective may lead to a biased control strategy that some of the participants may not follow and the benefits of some participants are impaired.

The comparison of different distribution planning models is summarized in Table I. The novel distribution system planning scheme proposed in this paper is devised based on the probabilistic evaluation of system risk by upgrading system infrastructure to acceptable levels of reliability at the lowest possible cost (including infrastructure investment cost, compensation cost to control acceptance and operation cost after system upgrade). Reliability worth assessment [30] incorporates the interruption cost, investment, and operation cost analysis, and quantitative reliability assessment into an overall cost minimization procedure searching for mutual benefits between the grid operator and EV users. Interruption cost is adopted in [30]-[31] to provide an indirect measurement of reliability worth whereas the content of interruption cost shall be modified in accordance to the V2G application proposed in this paper. The main contributions of this paper include:

1). The stochasticity of EV traveling/charging behavior is fully analyzed with probabilistic techniques under the combined model of the transportation network and power grid.

2). The response of EV users to system control signals is clarified with the concept of customer damage cost (CDC). The planning scheme is therefore devised based on "dgrees of customer acceptance to potential control" rather than the usual "yes or no" logic.

3). By taking the amount of compensation to users into ac-

Table II
POSSIBLE SCENARIOS FOR PUBLIC CHARGING PREFERENCE

Public charging preference	Definition
No	$E_n^i = E_{n,\min}^i$, for $\forall i$
Moderate	E_n^i *obeys* $U(E_{n,\min}^i, E_{n,\max}^i)$, for $\forall i$
High	$E_n^i = E_{n,\max}^i$, for $\forall i$

count in the reliability worth assessment of distribution system planning, grid regulators are able to determine the trade-off between encouraging more control acceptance and investing more in infrastructure for optimal overall cost.

4). This paper is the first to quantitatively analyze the importance of user behavior consideration on the overall cost of distribution system planning.

The rest of the paper is organized as follows. In Section II, a general model for forecasting residential EV charging demand is formulated. In Section III, modeling of the V2G profile is proposed considering EV user behavior and the corresponding system control signal. A comprehensive planning cost analysis is given in Section IV that takes customer compensation cost into account. The planning optimization procedure is provided in Section V and its effectiveness is assessed by numerical studies in Section VI. Section VII concludes the paper.

II. MODELING OF EV CHARGING DEMAND

This section outlines a general probabilistic technique for forecasting daily EV charging demand. As EV user behavior is stochastic, gathering the forecast information is crucial to regulators.

A. Travel Route Modeling

Daily trips that start and end at residential areas (H) are classified into different travel purposes, including trips transiting between districts $\{\mathrm{A}_n\} = \{\mathrm{A}_1, \mathrm{A}_2, ..., \mathrm{A}_N, \mathrm{A}_\mathrm{H}\}$ (for public places n=1,…, N; for residential areas n=H). Each district is equipped with an aggregator that connects to one bus in the distribution network and integrates local charging/discharging facilities. An EV may perform several trips a day, and the series trip chain is described in Fig.1. By using the data from local travel surveys, the output of travel route modeling includes the forecast for each trip end time in the trip chain $\{T_{\mathrm{c},n}^i\} = \{T_{\mathrm{c},1}^i, T_{\mathrm{c},2}^i, ..., T_{\mathrm{c},N}^i, T_{\mathrm{c,H}}^i\}$ and each travel distance $\{l_{n,\,n+1}\}$. For details of the travel route modeling, the reader is referred to our previous work [4]. If the average urban driving speed is v, the trip start time at place n can be estimated as:

$$S_n^i = T_{\mathrm{c},n+1}^i - \frac{l_{n,n+1}^i}{v} \tag{1}$$

B. Charging Behavior Modeling

For the i^{th} EV, which starts in a fully charged state from A_H and travels along the series trip chain, constraints exist for the amount of energy charged at public places. First, the energy charged at each stop should not exceed the total state of charge (SOC) deficit; second, there should be enough SOC for the next trip after charging. For a day's final destination at H, EV users would fully charge their batteries before the start of the next day's trip. Equations (2), (3) and (4) are constituted to reflect these respective constraints (H can be regarded as place 0 or N+1):

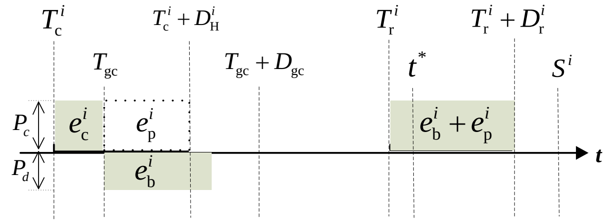

Fig. 2 Timeline and energy flow of V2G control

$$\begin{cases} E_1^i \le \omega \cdot l_{\mathrm{H},1}^i \\ E_2^i \le \omega \cdot (l_{\mathrm{H},1}^i + l_{1,2}^i) - E_1^i \\ \cdots \\ E_N^i \le \omega \cdot \sum_{n=1}^{N} l_{n\text{-}1,n}^i - \sum_{n=1}^{N-1} E_n^i \end{cases} \tag{2}$$

$$\begin{cases} E_1^i \ge \max\{0, \omega \cdot (l_{\mathrm{H},1}^i + l_{1,2}^i) - B_\mathrm{c}\} \\ E_2^i \ge \max\{0, \omega \cdot (l_{\mathrm{H},1}^i + l_{1,2}^i + l_{2,3}^i) - E_1^i - B_\mathrm{c}\} \\ \cdots \\ E_N^i \ge \max\{0, \omega \cdot \sum_{n=1}^{H} l_{n\text{-}1,n}^i - \sum_{n=1}^{N-1} E_n^i - B_\mathrm{c}\} \end{cases} \tag{3}$$

$$E_\mathrm{H}^i = \omega \cdot \sum_{n=1}^{\mathrm{H}} l_{n\text{-}1,n}^i - \sum_{n=1}^{N} E_n^i \tag{4}$$

where ω is the energy consumption per km, E_n^i is the energy to be charged at place n, and B_c is 80% of the total capacity of EV batteries. As the potential charging energy at public places is defined in a range, as reflected in (2) and (3), three possible scenarios are assumed in Table II to represent different user preference.

In this paper, only the residential charging demand E_H^i is considered in the distribution system (the charging place parameter n is therefore omitted in the following analysis) but it will be greatly influenced by the stochastic charging behavior at public places as shown in (4). The charging duration D_H^i at home is calculated in (5):

$$D_\mathrm{H}^i = \frac{E_\mathrm{H}^i}{\kappa_\mathrm{c} \cdot P_\mathrm{c}} \tag{5}$$

where P_c and κ_c are the charging power and efficiency, respectively.

III. MODELING OF V2G PROFILE

This section describes the prerequisites for performing V2G, namely, the fulfillment of individual customer damage cost

(CDC), temporal feasibility for discharging, and enough time for recharging after V2G.

A. Amount of Compensation to Customers

For EV customers, accepting V2G control may raise privacy concerns, influence convenience, and affect EV battery life. In fact, the flexible pricing proposed in [12]-[14] may not naturally make all customers charge during the low-tariff period because their attitude towards the revenue gained by accepting control is fairly arbitrary. A comprehensive customer survey is conducted in [30] to quantify user behavior by investigating customer's willingness to pay to avoid a power interruption and the willingness to accept compensation for having had one. The amount of CDC obtained from the survey directly portrays the unit interruption compensation ($/kWh) claimed by individual customers.

In this paper, CDC can be regarded as the extra amount of compensation claimed by EV customers for obeying V2G control in addition to the revenue gained from flexible pricing. The average and standard deviation of CDC for residential EV customers are represented by μ_c and δ_c. For the i^{th} customer, the CDC is ξ^i which follows the normal distribution [30] shown in (6):

$$\xi^i \ \ obeys \ \ N(\mu_c, \delta_c) \tag{6}$$

Before undertaking system planning for future years, the grid operator should have carefully investigated the habits of local EV customers. The parameters μ_c and δ_c are assumed to be known to the grid operator and the best compensation ratio γ_λ at the λth year is determined based on the information. Therefore, $\gamma_\lambda \cdot \mu_c$ represents the unit V2G compensation rate at the λth year and only those users fulfilling (7) potentially consider accepting V2G control [30].

$$\xi^i \le \gamma_\lambda \cdot \mu_c \tag{7}$$

B. Energy Amount for Discharging

Fig. 2 shows the timeline of V2G control for the i^{th} EV. T_{gc} and D_{gc} are the grid control start time and the lasting period, respectively. The original charging arrangement, charging start time T_{c}^i and duration D_{c}^i vary among different users but V2G is temporally feasible only if the trip end time T_{c}^i is satisfied according to:

$$T_{\text{c}}^i \le T_{\text{gc}} + D_{\text{gc}} \tag{8}$$

For those EVs under control, e_{p}^i, the part of original charging arrangement falling within the period [T_{gc}, T_{gc}+D_{gc}] should be postponed. The residual battery energy $e_{residual}$ at time T_{gc} is calculated using (9) and the energy discharged back e_{b}^i during [T_{gc}, T_{gc}+D_{gc}] is determined in (10):

$$e_{\text{residual}} = B_{\text{c}} - E_{\text{H}}^i + e_{\text{c}}^i \tag{9}$$

$$e_{\text{b}}^i = \min\left(e_{\text{residual}}, \frac{P_{\text{d}}}{\kappa_{\text{d}}} \cdot (T_{\text{gc}} + D_{\text{gc}} - \max(T_{\text{c}}^i, T_{\text{gc}}))\right) \tag{10}$$

where e_{c}^i is the energy already charged at H before T_{gc} ($e_{\text{c}}^i = 0$ if $T_{\text{c}}^i > T_{\text{gc}}$). P_{d} and κ_d are discharging power and efficiency, respectively.

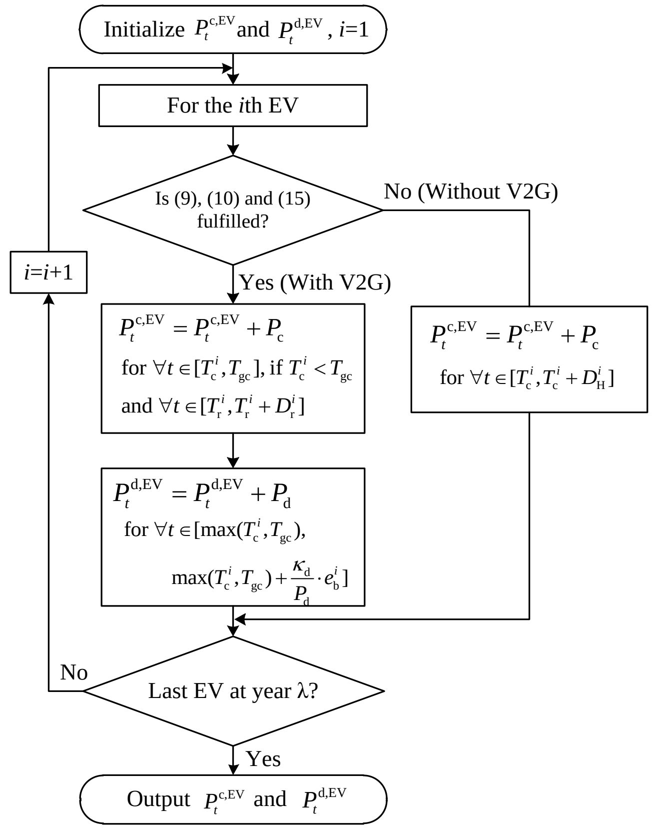

Fig. 3 Flowchart for power aggregation

C. Recharging Demand after V2G

One of the premises for V2G control is that the normal activity of EVs ought not to be affected. Therefore, EVs should be recharged to fulfill the original charging demand after the V2G control period. The time needed for recharging is calculated using:

$$D_{\text{r}}^i = \frac{e_{\text{b}}^i + e_{\text{p}}^i}{\kappa_{\text{c}} \cdot P_{\text{c}}} \tag{11}$$

where D_{r}^i is recharging duration of EV i; e_{p}^i is Postponed original charging demand of EV i.

Experiments suggest that recharging immediately after the termination of control will create another power demand peak ensuing time T_{gc}+D_{gc}. Unlike other existing works, this paper puts forward the concept of reference recharging time t*. Considering the urgency of and fairness to each EV customer, the recharging start time T_{r}^i for the i^{th} EV based on t* is given by:

$$T_{\text{r}}^i = t^* + h_1 \cdot (S^i - t^* - D_{\text{r}}^i) - h_2 \cdot (t^* - T_{\text{c}}^i) \tag{12}$$

where h_1 associates with urgency, in that EVs with less spare time before the start of next trip are assigned earlier charging, and h_2 associates with fairness, i.e., the regulators assign relatively earlier recharging start times to EVs plugging in earlier.

The following constraint (13) guarantees that recharging will complete before the start of next trip:

$$T_{\text{r}}^i + D_{\text{r}}^i \le S^i \tag{13}$$

Table III

ILLUSTRATION OF PLANNING OPTIMIZATION PROCEDURE

Step 1	Input distribution system topology, EV travel statistics, charging behavior at public stations (2)-(3), and CDC distribution (6).
Step 2	Generate the chromosomes with control variables T_{gc}, D_{gc}, i^*, and γ_λ for each planning year.
Step 3	Obtain T_c^i, D_c^i, S^i and ξ^i for all EVs penetrating the system at year λ by using the probabilistic technique proposed in Sections II and III.A.
Step 4	Obtain the V2G profile for year λ with (6)-(13) corresponding to the control variables.
Step 5	Repeat Steps 2-4 for all Y years over the planning horizon. It should be noted that the base load and the number of EVs penetrating the system increase with each successive year.
Step 6	Calculate the total planning cost from (14)-(23).
Step 7	Repeat Steps 3-6 with the Monte Carlo method and obtain the expected total planning cost corresponding to the chromosomes.
Step 8	Perform selection, crossover and mutation to generate chromosomes of the next generation.
Step 9	Repeat Steps 2-8 until maximum generation is reached or no improvement found for several generations to obtain the optimal planning scheme with the least cost.
Step 10	Perform a stability evaluation for the obtained planning scheme with indices including the minimum nodal voltage V_{min} and expected energy not supplied (EENS) [11], [20], [30] for the whole planning horizon.

D. Aggregated Charging and Discharging Profile

The aggregated charging power $P_t^{\mathrm{c,EV}}$ and discharging power $P_t^{\mathrm{d,EV}}$ are obtained via the process presented in Fig. 3 by superposition of the individual charging/discharging power of all EVs performed at each time of the day. Fig. 3 shows that the aggregated load profile is greatly influenced by EV behavior and system control scheme defined by (7), (8) and (13).

IV. COST ANALYSIS FOR DISTRIBUTION SYSTEM PLANNING

Differing from the planning models proposed in [17]-[29], the cost analysis in this paper simultaneously ponders the mutually influenced parts, including operation cost, V2G compensation cost and infrastructure investment cost, and obtains the trade-offs among them. According to the variation of baseload demand and number of EVs integrated each year, the local regulator can control the overall V2G profile by adjusting the compensation ratio γ_λ to satisfy system stability requirements and total cost reduction.

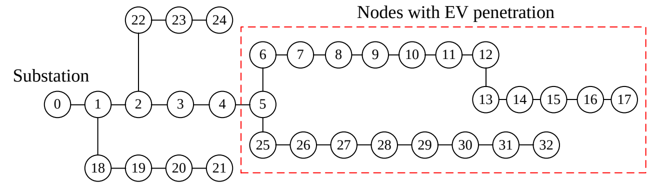

Fig. 4 32-bus distribution test system

The total cost of the Y-year distribution system planning is given as follows:

Objective:

$$\min \; f = f^{oper} + f^{cc} + f^{inv} \tag{14}$$

$$f^{oper} = d^{\text{annual}} \sum_{\lambda=1}^{Y} \Big(\sum_{t\in\Omega^t} (\rho_t^{\text{da}} + \rho^{\text{CO}_2}) P_{t,\lambda}^{s} + \rho^{\text{NL}} \sum_{t\in\Omega^t} P_{t,\lambda}^{loss} \Big) \tag{15}$$

$$f^{cc} = d^{\text{annual}} \sum_{\lambda=1}^{Y} \Big(\gamma_\lambda \mu_{\text{c}} \cdot \sum_{i}^{q_\lambda} e_{\text{b}}^{i} \Big) \tag{16}$$

$$\begin{aligned} f^{inv} =& Y \cdot [\pi^{LL} (\rho^{EL} + \rho^{CL} \sum_{xy\in\Omega^l} P_{xy,\text{cap}}^{l}) \\ &+ \pi^{LS} (\rho^{ES} + \rho^{CS} \sum_{x\in\Omega^s} P_{x,\text{cap}}^{s})] \end{aligned} \tag{17}$$

where

$$P_{xy,\text{cap}}^{l} = P_{xy,\max}\,, \qquad \forall xy \in \Omega^l \tag{18}$$

$$P_{x,\text{cap}}^{s} = P_{x,\max}\,, \qquad \forall x \in \Omega^s \tag{19}$$

$$\pi^{LL} = \frac{\varepsilon(1+\varepsilon)^{LL}}{(1+\varepsilon)^{LL} - 1}\,, \quad \pi^{LS} = \frac{\varepsilon(1+\varepsilon)^{LS}}{(1+\varepsilon)^{LS} - 1} \tag{20}$$

subject to:

$$\begin{aligned} & P_{x,t}^{s} - (P_{x,t}^{\text{c,EV}} - P_{x,t}^{\text{d,EV}} + P_{x,t}^{\text{base}}) \qquad \forall x \in \Omega^x, \forall t \in \Omega^t \\ &= U_{x,t} \sum_{y\in\Omega^n} U_{y,t} (G_{xy} \cos\theta_{xy,t} + B_{xy} \sin\theta_{xy,t}) \end{aligned} \tag{21}$$

$$\begin{aligned} & Q_{x,t}^{s} - Q_{x,t}^{\text{base}} \qquad \forall x \in \Omega^x, \forall t \in \Omega^t \\ &= U_{x,t} \sum_{y\in\Omega^n} U_{y,t} (G_{xy} \sin\theta_{xy,t} - B_{xy} \cos\theta_{xy,t}) \end{aligned} \tag{22}$$

$$U_{\min} \le U_{x,t} \le U_{\max} \tag{23}$$

The objective function (14) aims to minimize the overall operation cost f^{oper}, customer compensation cost f^{cc} and investment cost f^{inv} across the planning horizon. The operation cost in (15) is composed of the electricity purchase cost from the wholesale market and the network line loss cost. d^{annual} is the number of days in one year. ρ_t^{da}, ρ^{CO_2}, and ρ^{NL} represent the day-ahead electricity price at time t, the fixed carbon tax rate, and unit line loss rate, respectively. $P_{t,\lambda}^{s}$ and $P_{t,\lambda}^{loss}$ denote the total power demand at the substation and the total system line loss power, respectively. The total cost of customer compensation is calculated in (16) where q_λ represents the number of total EV users fulfilling all the prerequisites (7), (8) and (13) at year λ with compensation ratio γ_λ.

Table IV
SYSTEM PLANNING PARAMETERS

Symbol	Value	Symbol	Value
a	0.05	b	0.1
LL	15 years [17]	LS	15 years [17]
ρ^{CO_2}	\$0.0092/kWh [17]	ρ^{NL}	\$0.036/kWh [17]
U_{min}	0.95 [17]	U_{max}	1.05 [17]
P_c	3.3 kW [4]	P_d	3.3 kW [4]
ω	0.24 kWh/km [4]	B_c	0.8×30 kWh

In (17), the equivalent total infrastructure investment cost for the planning horizon is presented. The adequate capacities of feeders $P^{l}_{xy,\text{cap}}$ and substation $P^{s}_{x,\text{cap}}$ are appropriately planned by satisfying the maximum power flow at line xy (18) and maximum power demand of the substation located at node x (19) over the Y-year planning horizon. ρ^{EL}, ρ^{ES} and ρ^{CL}, ρ^{CS} are the engineering, procurement and construction (EPC) fixed cost and capital cost, respectively for constructing feeders and substations. π^{LL} and π^{LS} calculated from (20) transform the construction cost of feeders and substations into annuities which are related to the interest rate ε and their respective lifespans LL and LS .

The AC power flow equality constraints are depicted in (21) and (22). $P^{\text{c,EV}}_{x,t}$, $P^{\text{d,EV}}_{x,t}$, and $P^{\text{base}}_{x,t}$ are the charging, discharging, and base power load, respectively, at node x time t. The nodal voltage constraint is given in (23).

V. PLANNING OPTIMIZATION PROCEDURE

For a given system with annual load growth rate a and EV penetration growth rate b, the total cost of distribution system planning depends on the power load profile each year, the compensation paid to customers for improving the load profile, and the infrastructure investment required to satisfy the maximum load demand over the planning horizon. As the EV charging demand and V2G profile are really stochastic, the Monte Carlo method [30] is adopted for error reduction and reliability evaluation. To be consistent with our previous work in [4], the same EV travel behavior forecast (Section II.A) is carried out whereas the general charging behaviors before arriving home (2) and (3) are assumed to be known to the local grid operator. The optimization procedure for the Y-year system planning is summarized in Table III:

VI. NUMERICAL STUDIES

A. Test System and Basic Data

To assess the effectiveness of the proposed planning optimization algorithm, the 32-bus radial distribution system shown in Fig. 4 [32] is chosen because, as stated by *M. E. Baran*, "The system is not well-compensated and lossy". For a planning horizon of 5 years (Y=5), the obsolete feeders and the substation at Bus-0 shall be completely replaced to satisfy load growth and increasing EV penetration. This distribution system is designed to supply power to residential customers. The residential EVs cover the nodes of 5 to 17 and 25 to 32, and are distributed among the nodes based on the proportions of base power load at those nodes. For the analysis of EENS for all nodes with EV penetration, the failure rate of the feeder at line 4-5 is assumed to be 0.065 faults/year [20] and the repair time is 1 hour.

Table V
PLANNING WITH DIFFERENT INITIAL EVS

Initial EVs	f^{oper} (\$×10^6)	f^{cc} (\$×10^5)	f^{inv} (\$×10^6)	f (\$×10^6)	V_{min} (p.u.)
0	5.073	0	1.037	6.110	0.9428
500	5.186	1.096	1.021	6.316	0.9614
1000	5.381	1.531	1.026	6.559	0.9555

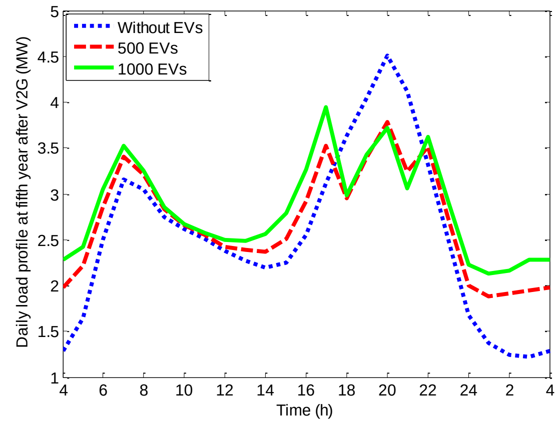

Fig. 5 Comparison with respect to initial EV penetration

Daily variation of the residential base load is collected from the Residential Energy Consumption Survey [33] and the variation of day-ahead electricity price is obtained from PJM data [34]. The EV travel behavior is derived from the 2009 National Household Travel Survey (NHTS) [35]-[36]. The data for infrastructure investment costs ρ^{EL}, ρ^{ES}, ρ^{CL} and ρ^{CS} are derived from [21]. As the EPC fixed costs ρ^{EL} and ρ^{ES} are much higher than the capital costs ρ^{CL} and ρ^{CS}, the capacity of feeders and substations should be sufficient for the entire 5-year development and therefore reconstruction is avoided. The standard deviation of CDC is in fixed relation to the mean value (δ_c=0.5μ_c). Other parameters are listed in Table IV.

In the base case, the initial number of EVs penetrating the grid in the first year is 1000. Charging at public places is moderately preferred and the mean value of CDC μ_c=0.02. The efficiency of the planning optimization is assessed based on cases with different initial EV penetration, user charging preference, and CDC distribution. For each case, only one variable changes while the others keep the same as in the base case.

B. Planning with Different Initial EV Penetration

When the initial number of penetrating EVs increases, both the charging demand and the potential energy for V2G grow

Table VI
PLANNING WITH DIFFERENT CHARGING PREFERENCE

Public charging preference	f^{oper} (\$×10^6)	f^{cc} (\$×10^5)	f^{inv} (\$×10^6)	f (\$×10^6)	V_{min} (p.u.)
No	5.667	1.820	1.028	6.876	0.9515
Moderate	5.381	1.531	1.026	6.559	0.9555
High	5.168	1.500	1.018	6.337	0.9590

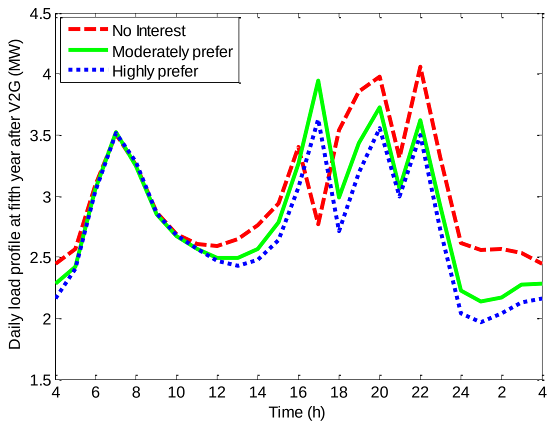

Fig. 6 Comparison with respect to charging preference

accordingly. The planning comparison is shown in Table V with the initial EV penetration changing from 0 to 500 to 1000. The annual growth rates of the base load and EV penetration are given in Table IV and remain the same for all cases.

Table V demonstrates that the system operation cost increases with the augmentation of EV penetration because the total daily power demand increases with the number of penetrating EVs regardless of V2G scheduling. Both the infrastructure investment cost and the minimum nodal voltage with V2G control are significantly improved by the proposed planning optimization compared to the case without EVs because the annual peak load demand is largely reduced.

The comparison of system-wide daily power demand profiles in the fifth year is shown in Fig. 5 as an example to demonstrate the effectiveness of the proposed optimal planning. Considering the growth of base load and EV penetration during the planning horizon, the blue dotted line denotes the trend of baseload power derived from [33]. Corresponding to the result in Table V, its peak load is so high that more investment in feeders and substations is required. For the two cases with EV penetration, their V2G control intervals are both constrained from 18:00 to 22:00, which greatly improves the peak load profiles with acceptable compensation paid to users. The load profiles from 17:00 to 22:00 follow a zig-zag trend because the compensation ratio γ_λ is kept the same during the whole control period. For example, raising γ_λ at 20:00 will be unfair to those starting V2G earlier and will discourage them from accepting V2G at an earlier hour. Furthermore, the recharging arrangement proposed in Section III.C works efficiently and makes the recharging demand of all controlled EVs well-distributed

Table VII
PLANNING WITH DIFFERENT CDC DISTRIBUTIONS

μ_c	f^{oper} (\$×10^6)	f^{cc} (\$×10^5)	f^{inv} (\$×10^6)	f (\$×10^6)	V_{min} (p.u.)	EENS (kWh)
0	5.130	0	1.025	6.155	0.9562	55.817
0.01	5.233	1.795	1.025	6.438	0.9559	55.673
0.02	5.381	1.531	1.026	6.559	0.9555	55.619
0.03	5.467	1.217	1.027	6.616	0.9551	55.643
∞	5.673	0	1.054	6.727	0.9230	55.819

within the low-tariff period (from 24:00 to 7:00).

C. Planning with Different Charging Preference

The charging preference in public places can be stochastic, as shown in (2) and (3). The relationship between public charging preference and residential charging demand is demonstrated in (4). A planning comparison of the three charging preference scenarios specified in Table II is shown in Table VI.

Although the residential charging demands of the three cases are fairly different, the planning optimization proposed efficiently raises the minimum voltage to meet the system stability requirement (23). The case of no interest in public charging means that EV users will only keep the battery energy above the minimum SOC that can support their next trip. As a result, the residential charging demand will increase significantly, as inferred from (4), making the operation cost and infrastructure investment of this case higher compared to the other two cases.

For the daily load comparison of the fifth year shown in Fig.6, the proposed planning optimization successfully lowers the peak load to an acceptable level and makes the recharging demand well-distributed in the low-tariff periods regardless of the charging preference. For the case with no interest in public charging, the residential charging demand is so high such that the V2G control starts earlier, i.e., 17:00 instead of 18:00. As a result, the power load at 17:00 is significantly reduced compared to the peak loads of the other two cases at that time. With respect to the cases with a moderate and high preference for public charging, variation trends in the load profile with V2G control are largely the same.

D. Planning with Different CDC Distributions

In this section, the optimal planning scheme varies with different CDC distributions. The planning comparison in Table VII is made among the cases of full cooperation between grid operator and EV customers (μ_c=0), μ_c=0.01 to 0.03, and the case of no cooperation whatsoever (μ_c=∞, equivalent to the case without V2G).

Based on Table VII, the operation cost decreases with the reduction of μ_c due to the fact that when less CDC is claimed by EV customers, a relatively larger compensation ratio γ_λ can be applied to attract more control acceptance. The electricity purchase cost and network line loss cost will simultaneously decrease owing to the control that more power can be discharged back in busy hours and recharged at valley periods. The fact that many more customers will be attracted to accept V2G control when μ_c is lower also makes the total

Table VIII
PLANNING WITH DIFFERENT CHARGING PREFERENCE

Case	f^{oper} (\$×10^6)	f^{cc} (\$×10^5)	f^{inv} (\$×10^6)	f (\$×10^6)	V_{min} (p.u.)
Wrong EVs charge at H	5.313	1.236	1.027	6.464	0.9583
Wrong EVs accept V2G	5.487	1.235	1.029	6.640	0.9551
Accurate forecast	5.381	1.531	1.026	6.559	0.9555

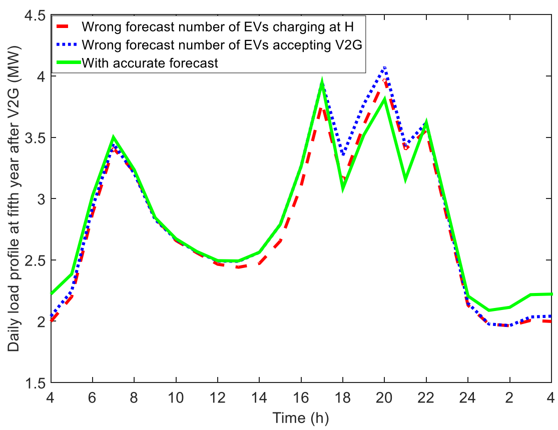

Fig. 7 Comparison with respect to EV user behavior

compensation cost f_{cc} increases from \$1.217 × 10^5 to \$1.795×10^5 when μ_c decreases from 0.03 to 0.01.

For the case with no cooperation, no EV users will obey the control signals but charge upon arrival at home instead. The operation cost and investment cost are both the highest among all cases because of the coincidence of base peak load and EV charging peak load. Moreover, the minimum nodal voltage will drop to as low as 0.9230, which contravenes constraint (23). EENS also increases considerably compared to the cases with μ_c=0.01 to 0.03. Thus, a complete lack of cooperation between grid operator and EV customers will not only increase the total planning cost but also make system unstable.

The total planning cost is the lowest for the case with full cooperation. Note that this scenario conforms to the hypothesis proposed in [15]-[16], in that users are fully responsive and the cost decrement will be allocated to users. Here, the planning cost reduction is considered without variation of electricity purchase cost (as CDC is claimed in addition to the revenue from flexible pricing). Changing from the case with μ_c=∞ to that with μ_c=0, the planning cost reduction is \$2.126×10^4 with a total of 2.007×10^7 kWh discharged over the entire planning horizon. It is calculated that only \$0.0016/kWh can be allocated to users accepting V2G control. This amount of compensation is so small compared to the residential electricity price that only the revenue from flexible pricing cannot guarantee the "full responsiveness" of all users. Furthermore, excess discharging will create another recharging peak during the original valley hours so that the EENS is higher than for the cases with μ_c=0.01 to 0.03.

E. Cases with insufficient concern on user behavior

Grid operator shall make specific control strategy responding to different user behaviors. In this section, the comparison among the case with wrong forecast number of EVs charging at H, the case with wrong forecast number of EVs accepting V2G and the case with full consideration on EV user behavior is conducted to assess the significant influence of insufficient concern on EV user behavior.

As this paper proposes a long-term distribution planning that cannot respond to real-time charging demand variation, grid operator should have carefully investigated the number of EVs, growth rate, distribution of CDC, traveling and charging behavior in order to devise control or infrastructure upgrade strategy in advance. Failing to work out the practical and accurate forecast of EV user behavior will weaken the effectiveness of V2G control.

In the base case with an accurate forecast of EV user behavior, the daily load profile at fifth year after V2G is shown as the green line in Fig. 7. If the forecast lacks practical consideration on EV traveling and charging behavior, for example, the actual number of EVs charging at H is 20% less than estimated, the daily load profile changes to the red line as a result. Although the overall load is decreased because of the decline of actual EV charging, there will be insufficient EV users responding to V2G control signal that its peak is higher than the case with an accurate forecast. It is shown in Table VIII that wrong forecast number of EVs charging at H will lead to peak increase and potential augmentation of infrastructure investment.

On the other hand, if the operator has the wrong estimation on distribution of local CDC, for example the preset compensation rate attracts 20% less EVs accepting V2G control than estimation, EVs providing V2G support will not be enough when maintaining the original customer compensation rate that the load profile during the whole V2G control period will be much higher and denoted by blue dotted line in Fig. 7. As shown in Table VIII, it is apparent that failing to figure out how local users accept V2G compensation rate, i.e. the distribution of CDC, will largely increase the total cost by 1.2% to \$6.64×10^6 due to the peak increase during control hours. Besides, the grid minimum voltage is decreased that the stability margin of the grid is impaired.

VII. CONCLUSION

This paper puts forward an innovative idea that takes cognizance of stochastic user behavior in the realm of distribution system planning. This paper has successfully drawn the following three major conclusions:

1). The proposed method is able to forecast EV charging and V2G demand considering user behavior in a practical way.

2). The proposed optimization method for distribution system planning is proved effective in solving the trade-off between V2G incentive control and grid infrastructure investment under different initial EV penetration, charging preference or distribution of CDC.

3). It is the first attempt to quantitatively obtain the importance of user behavior consideration: 20% less EVs accepting V2G control than expected corresponds to 1.2% increase in total grid cost in the case study.

The mere revenue from flexible pricing is proved to be insufficient for attracting "full responsiveness" of all users. It is of great importance to investigate the charging behavior and CDC of local EV users in advance for the reliability worth assessment proposed in this paper. With appropriate customer compensation and system planning scheme, the total planning cost is the lowest with an acceptable reliability level.

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