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ORIGINAL RESEARCH PAPER

Decentralized stochastic programming for optimal vehicle-to-grid operation in smart grid with renewable generation

Yue Wang | Hao Liang | Venkata Dinavahi

Department of Electrical and Computer Engineering, University of Alberta, Edmonton, Canada

Correspondence
Yue Wang, Department of Electrical and Computer Engineering, University of Alberta, Edmonton, Canada.
Email: ywang15@ualberta.ca

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Abstract

This paper presents a decentralized stochastic programming operation scheme for a vehicle-to-grid system in a smart grid, which includes a series of equipment with random power generation and demands. For households with electric devices, renewable solar power generation, energy storage systems and electric vehicles, we consider utility operating expenses, including power loss and energy consumption cost as the objective function. For customers, we consider the cost of electricity, including battery degradation. To investigate the uncertainty of the devices, a bottom-up approach is proposed to develop a random device usage model for analyzing customers' uncertain behaviour. Besides, a random renewable power generation model and an electric vehicle random driving model are implemented. The proposed approach is implemented with OpenMP to simulate the decentralized process on a multi-core CPU while reducing the computational burden. A case study based on the IEEE 33-bus distribution system with different scenarios is used to evaluate the performance of the proposed approach. The simulation results show that by introducing an optimal household operation schedule, the expense of distribution system utility company can be reduced in which both customers and operators can benefit from the optimization of the system schedules.

1 | INTRODUCTION

Electric vehicles (EVs) [1] are becoming the primary means of reducing carbon dioxide emissions if they can be recharged by renewable power generation compared to conventional internal combustion engine vehicles. In addition, compared with traditional community shared storage, EV, as a kind of mobile storage, can be used as a family private storage unit to charge and discharge at home, and can serve as an additional storage unit for community shared battery storage. According to different incentive policies, the total number of EVs will reach 220 million by 2030, compared with the current number of 3 million [2]. However, since EV charging consumes a large amount of power, this can lead to higher peak grid consumption. In addition, the randomness associated with EV driving makes the EV optimization problem more challenging to solve.

There is a lot of research that studies EV charging methods as well as infrastructure analysis in response to incentive policies. Basically, recent research on EV optimization can be classified into two categories by different charging locations: charging EV at charging stations or charging EV at home. Specifically, for the charging station optimization problem, authors in [3] proposed a framework to optimize the bidding strategy of an ensemble of charging stations equipped with an energy storage system in the day-ahead power market. EV charging stations with renewable generation are discussed in [4]. By providing limited information to the proposed optimization framework, the system cost can be dramatically reduced compared to the benchmark. Besides, similar to EV charging stations, the EV parking lot allocation problem has been solved in [5].

For the optimization of home energy systems considering charging EVs at home, recent research works discusses how to minimize power loss in a smart home energy management [1, 6], which can help achieve more efficient grid operation . The authors in [7, 8] take renewable energy and local energy storage into consideration, seeking a minimum electricity cost while satisfying household energy demand and EV charging requirements. Moreover, by charging or discharging EVs, home energy management can minimize energy costs by considering estimates of household power demand or considering home climate energy cost [9, 10].

According to the technical literature, considerable research has provided impressive models for EV optimal operation. However, combined scheduling of different types of household appliances, renewable energy resources, EV operations and energy storage operations, while considering the operating expenses of utility, has not yet been resolved. Moreover, when considering EVs and renewable generation units, the scale of the problem has become dramatically large. The contributions of this article can be summarized as follows:

1. A stochastic model is proposed to determine the uncertain behaviour of household appliances load demands, EV driving model and distributed renewable resources, and modelling the home energy management system using stochastic formulation.
2. In order to describe the uncertain relationship between households and utility companies, we developed a bi-level stochastic programming model to determine the optimal household operating schedule. In addition, to reduce computational complexity, we implemented problem decomposition and scenario reduction technique in the proposed problem.
3. Decentralized computing is applied to accelerate the proposed approach. Our decentralized bi-level structure quantifies the cost-saving of utility as well as EV operation with renewable generation, while protecting customers' privacy.

The rest of this paper is organized as follows. The existing literature is reviewed in Section 2. Section 3 presents the problem formulation for each element in a distribution system. Section 4 introduces the problem formulation using a bi-level stochastic linear programming to achieve an economic goal for both utility companies and customers. Section 5 presents the decentralized bi-level stochastic linear programming. In Section 6, a case study with the IEEE 33-bus test distribution system is carried out. The conclusions are drawn in Section 7.

2 | RELATED WORK

When considering random features such as household appliances and EV operations, which related to human activities, or random renewable generation, the massive set of scenarios makes the optimal operation in a distribution very difficult to solve. Compared with the load demand optimization of household appliances, EV needs more energy to charge. Therefore, it is critical to consider the randomness of EV operation. There are many uncertainties regarding the operation of EV, such as drivers' departure/arrival time uncertainty [11], energy consumption uncertainty caused by drivers' different driving habits [6, 12], charging station access uncertainty and traffic flow uncertainty [13] and market price uncertainty [3]. Specifically, considering the uncertain EV demand and the driver's arrival/departure times, a two-stage stochastic programming model is proposed in [13], which aims to maximize access to the location and capacity of public EV charging stations in urban areas. A similar study [12] discusses efficient and reliable access to EV charging stations, and considers the EV random usage model under real-time pricing in smart grids. Moreover, a stochastic energy-aware routing framework that considers the random effects of environmental factors is proposed in [14], in order to improve the sustainability of future electrified transportation systems. All these research works discussed EV charging problems under uncertain pricing schemes or uncertain environmental conditions in the distribution system, but ignored home EV charging problem under the consideration of household load demand.

There are a limited number of research works that discussed EV operation in household load demand optimization under uncertainties. In [1], by coordinating the EV charging process, minimized power loss and voltage deviation can be achieved. In this work, the total load demand is randomly selected from specific scenarios for simulation, without considering EV operation randomness. Refs. [6, 15] have a similar problem. When optimizing an EV under the situation that the household load is uncertain, the load demand for household appliances is usually regarded as a random value, which is not accurate enough in the home energy management system. Customers' different lifestyles or family composition will lead to different lifestyle habits. The appliances related to these habits will cause random load demand, which cannot be simulated using random values.

Based on the stochastic features mentioned above, the optimization problems are usually modelled as a stochastic programming problem [7, 13, 14], in order to find the optimal decision with the minimum cost or the optimal scheduling. To solve the massive set of uncertain scenarios, Monte–Carlo simulation [6, 11], roulette wheel mechanism [8] or scenarios selected from historical data [5] have been widely used in recent research works. But after all, it is ultimately some specific cases that are randomly selected from determined distributions.

On the other hand, to improve the efficiency of stochastic programming optimization, decentralized computing can potentially be used. Different from parallel computing, which relies on high-performance computers, decentralized computing distributes tasks to one or more computers. Specifically, to solve the large-scale optimization problem in smart grid operations, the authors of [16] proposed a decomposition algorithm using the MapReduce framework. The model can also be applied to the synchronized harmonics [17] or circuit switches [18] in distribution networks for big data analysis. The application in a smart grid can be used to optimize the control of distribution feeders with smart loads [19]. By distributing individuals from the master-node computer among worker-nodes to achieve minimal losses, the run-time can be significantly reduced simultaneously.

In this work, optimization issues in a distribution system with households equipped with renewable power generation, electric vehicle and backup storage units are investigated. Random features such as renewable power generation, uncertain house power consumption and uncertainties associated with EV driving will be modelled by a probabilistic model.

Decentralized computing is used for large-scale optimization. To reduce the computational complexity, problem decomposition and scenario reduction are implemented in this research.

3 | SYSTEM MODEL

Households in a typical smart grid consist of conventional electricity, electrical equipment, renewable energy generation, energy storage systems and EVs. In this section, we introduce the linear power flow model for the distribution system and household random components features.

3.1 | Linear power flow analysis

It is known that, for an N node distribution system, the complex power flow can be defined as

$$S_n = P_n + jQ_n = V_n I_n^*, \quad \forall n \in N \tag{1}$$

where P and Q represent real power and reactive power, respectively, while V and I refer to the node voltage phasor and current phasor, respectively. This equation shows that the complex power flow S is composed of real power and reactive power, which is equal to the product of voltage and the conjugate of the corresponding node current. In addition, it is known that current through the nodal admittance matrix Y is linearly related to the voltage, as indicated by $I = YV$. By assuming that the shunt admittances of the buses are negligible [20], we can derive the admittance matrix to satisfy $Y\mathbb{1} = 0$, where $\mathbb{1}$ represents the vector of ones. Moreover, by extending the linear relationship between voltage and current as

$$\begin{bmatrix} I_0 \\ I_n \end{bmatrix} = \begin{bmatrix} Y_{00} & Y_{0n} \\ Y_{n0} & Y_{nn} \end{bmatrix} \begin{bmatrix} V_0 \\ V_n \end{bmatrix}, \quad \forall n \in N \tag{2}$$

where node 0 refers to the PCC point and extension matrix Y is the admittance between nodes 0 and n, we can derive the following linear equation:

$$V_n = V_0\mathbb{1} + Y_{nn}^{-1} I_n, \quad \forall n \in N \tag{3}$$

where Y_{nn} is invertible because $\mathbb{1}$ is the only vector in the null space of Y. Consequently, by solving Equations (1) and (3), we can achieve power loss $\mathcal{L}$ as shown below:

$$\mathcal{L}_n = Y|V_n|^2, \quad \forall n \in N \tag{4}$$

3.2 | Home demand loads probabilistic model

Since most home electrical appliances require manual operation, we can define the random distribution of these devices through the random distribution of human activities. For example, we can define the probability distribution of oven or stove usage by human cooking probability distribution. In addition, the probability distribution of human activities also depends on the type of family, and the composition of the family can be found in [21].

In this work, we first define the household probability distribution of the daily activity by $\boldsymbol{\xi}_{m,t}$, where the subscript (m, t) represents the index of houses and the time slots, respectively. We assume that devices related to an identical activity follow the same probability and their activities are affected by the electrical price B_t. Therefore, the price-sensitive probability distribution profile can be expressed as

$$\boldsymbol{\xi}'_{m,t} = \sigma G(B_t) \cdot \boldsymbol{\xi}_{m,t}, \quad \forall m \in M, t \in T \tag{5}$$

where σ is the coefficient to maintain the summation of the new distribution is equal to 1, and $G(B_t)$ denotes to the price-sensitive function.

Due to the device distributions, the total household load consumption distribution $\boldsymbol{\zeta}_{m,t}$ of each time slot can be derived by the bottom-up approach. For appliance $a \in A$, we have the turn on probability $\xi_{a,t}$ at time t by the device distribution $\boldsymbol{\xi}_{m,t}$ (the probability of turn off device $a' \in A$ is $\overline{\xi}'_{a',t} = 1 - \xi_{a,t}$) and their rated power consumption. Then, we can have the power probability distribution at time t as follows:

$$\boldsymbol{\zeta}_{m,t} = \Pi_A \boldsymbol{\xi}'_{a',t} \cdot \overline{\boldsymbol{\xi}}'_{a,t}, \quad \forall a \cap a' = A, a \neq a' \tag{6}$$

Here, a and a' indicate the appliances which are turned on or off, respectively. And the corresponding power can be achieved as follows:

$$P^f_{m,t} = \sum_a P_{a,t}, \quad \forall a \in A, m \in M, t \in T \tag{7}$$

where the set $a \in A$ is identical to the one in (6). By defining the number of the scenarios $k \in K$, we can conclude the household power distribution as

$$\zeta^f_{m,k,t} = h^f(P^f_{m,k,t}), \quad \forall m \in M, k \in K, t \in T \tag{8}$$

3.3 | Renewable power generation model

Similar to the previous section, we can derive the solar power generation distribution by solar irradiance. Solar irradiance I_β [22] is related to a series of parameters, such as photovoltaics (PV) array inclination angle β, beam radiation ratio [23], reflectance of the ground, extraterrestrial solar irradiance, diffuse fraction and clearness indicator. With the relationship between diffuse fraction and clearness indicator, we can derive the probability density function (PDF) of the clearness indicator as introduced in [24] and the distribution of solar irradiance.

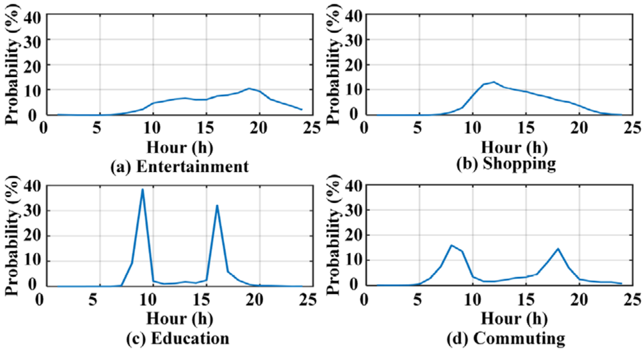

FIGURE 1 Travel start time by trip purpose distribution probability

As we mentioned, the PDF of PV active power output is related to solar irradiance and has several variables, such as the total area of the PV array area w and the cell temperature [25]. Moreover, according to [26], the temperature change of the PV cell is much slower than the rapid change of solar irradiance. Therefore, we ignore the influence of PV cell temperature and present the PV power output function as follows:

$$P^r_{m,t} = I_{\beta,t} w_m \eta^r, \quad \forall m \in M, t \in T \tag{9}$$

where η^r is the coefficient of the PV array efficiency. Therefore, the PDF of the PV power output $\xi^r_{m,t}(P^r_{m,t})$ can be calculated and is defined as

$$\xi^r_{m,t} = h^r(P^r_{m,t}), \quad \forall m \in M, t \in T \tag{10}$$

3.4 | EV probabilistic model

Different from other household electrical appliances, the randomness of EV is much more complicated to present directly due to uncertain driving patterns and different human behaviours in different lifestyles. To solve this problem, in this section, we first introduce the uncertainty features of EV, and then present the typical constraints of EV.

3.4.1 | EV usage probabilistic model

The random EV driving mode, such as the arrival and departure times of EV owner, driving distance, or the amount of EV battery remaining when people are arriving or departing, makes the establishment of the EV probability model more complicated.

To build an EV model that takes these random characteristics into account, we can derive the distribution of EV random usage time through the UK National Travel Survey [27], in which we can achieve the time and distance of people travelling. Depending on the purpose of the trip, we can analyze the start or end time of the trip based on Figure 1, and define these distributions as variable $\mathbf{t}^v$. Then, we can use this distribution to generate the operation time by start time t^u and the end operation time t^z, respectively. Thus, the start and end times of EV operations follow the distribution shown as

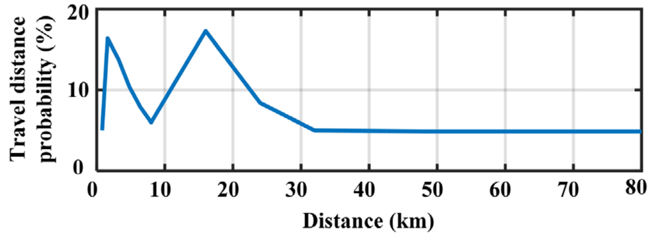

FIGURE 2 Travel distance probability distribution

$$\begin{aligned} t^u &= h^v(t^v), \\ t^z &= h^v(t^v), \end{aligned} \quad \forall (t^u, t^z) \in \mathbf{t}^v, t^z \geq t^u \tag{11}$$

$$t_{\text{flag}} = \left\{ \begin{array}{ll} 1, & \text{if} \quad t \in [t^u, t^z] \\ 0, & \text{otherwise} \end{array} \right) \tag{12}$$

Moreover, we can derive travel distance through the National Household Travel Survey [28]. And we define it by the random variable X and shown in Figure 2.

As we mentioned, the battery state before the operation is another stochastic variable. If given a distribution of the state of charge (SOC) at the starting time t^u, the battery state can be achieved by

$$E_t = \text{SOC} \cdot Z^v, \quad \forall t = t^u \tag{13}$$

Note that in this work, we do not consider EV charging in a parking lot or EV charging station, and only consider operation at home. Therefore, we should realize that if there is no one in the house ($t_{\text{flag}} = 0$), then unless people arrive home ($t_{\text{flag}} = 1$), EVs should not be used or optimized.

Moreover, it is worth noting that due to the lack of EV data, the survey data we implemented is applicable to all private vehicles, including traditional internal combustion engine vehicles, electric vehicles and hybrid vehicles.

3.4.2 | EV operation characterization

After determining the uncertain EV operating time and mileage of the usage, we can build the stochastic EV operating model through the EV battery charging and discharging process. First, during a specific time period $t \in [t^u, t^z]$, the EV charging or discharging process should not occur at the same time, and we define EV battery charging/discharging power limits and energy storage limits as follows:

$$\begin{aligned} &P^{vc}_t \cdot P^{vd}_t = 0, \quad \underline{P}^{vc} \leq P^{vc} \leq \overline{P}^{vc} \\ &\underline{P}^{vd} \leq P^{vd} \leq \overline{P}^{vd}, \quad \underline{E}^v \leq E^v \leq \overline{E}^v \end{aligned} \tag{14}$$

By defining the battery charging/discharging operation efficiency η^{vc} and η^{vd}, respectively, we can calculate the EV battery current state by

$$E_t^v = E_{t-\Delta t}^v + P_{t-\Delta t}^{vc} \cdot \eta^{vc} \cdot \Delta t + P_{t-\Delta t}^{vd} \cdot \eta^{vd} \cdot \Delta t \tag{15}$$

The equation shows that, the EV battery current state is related to the previous time state, and is also related to the amount of power required for charging/discharging operation during this period.

Moreover, the EV total energy charged should satisfy the next driving requirements shown as follows:

$$E^v = \sum_t E_t^v, \quad E^v \geq X * \eta^X \tag{16}$$

Here, the EV battery efficiency η^X can be achieved by analyzing the EVs available on the market. The details and parameters we introduced in this section will be presented in the simulation section.

Moreover, battery degradation is an essential indicator of maintaining battery health. Therefore, we consider it as follows:

$$D_t^v = \frac{\delta_1 \cdot \mathbb{E}(E_t)/Z^v - \delta_2}{\mathrm{CF} \cdot y \cdot 8760} \tag{17}$$

where δ_1 and δ_2 are linear fit coefficients; CF refers to the capacity fade, which is usually taken above to be 20%; y represents the battery life span; and Z^v represents the battery capacity. Finally, we can derive the total EV electrical cost, which includes the expense of charging or discharging process and the cost of battery degradation, given by

$$C^v = \sum_t (B_t \cdot P^{vc} - U_t \cdot P^{vd} + D_t^v), \quad t \in [t^u, t^z] \tag{18}$$

3.5 | Energy storage model

Houses equipped with renewable generation usually have alternate energy storage to store extra energy. Therefore, we consider some common storage characteristics, which should satisfy the following constraints:

$$\begin{aligned} &P_t^{xc} \cdot P_t^{xd} = 0, \quad \underline{P}^{xc} \leq P_t^{xc} \leq \overline{P}^{xc} \\ &\underline{P}^{xd} \leq P_t^{xd} \leq \overline{P}^{xd}, \quad \underline{E}^x \leq E_t^x \leq \overline{E}^x \end{aligned} \tag{19}$$

$$E_t^x = E_{t-\Delta t}^x + P_{t-\Delta t}^{xc} \cdot \eta^{xc} \cdot \Delta t + P_{t-\Delta t}^{xd} \cdot \eta^{xd} \cdot \Delta t \tag{20}$$

Similar to the EV operating constraints, battery operation should avoid simultaneous charging and discharging process, and can operate within a tolerable range, which is shown in Equation (19). In addition, we have the current battery state equation shown in Equation (20). Moreover, since the battery degradation for EV [Equation (17)] is calculated based on long-term data research results, it is suitable for most lithium-ion batteries. Therefore, we implement the same degradation model for energy storage.

Note that the difference between an EV and a battery storage is that the battery storage can be operated in all periods, and the operation does not require people to be at home. We assume the battery is a type of recourse appliance, which is dependent on the operation of other appliances. Therefore, battery operation costs can be derived as follows:

$$C^x = \sum_t (B_t \cdot P^{xc} - U_t \cdot P^{xd} + D_t^x), \quad t \in T \tag{21}$$

4 | PROBLEM FORMULATION

Considering that we are seeking for optimization of both customers and operators, a bi-level model can solve this problem simultaneously. Utility companies can determine the amount of power purchased from the customers in the upper level problem, with the maximum profits, while customers can decide their electrical devices usage in the lower level, aiming at minimizing the power consumption expenses.

Different from the standard bi-level model, such as the general formulation of the Stackelberg game, customers would compete with each other, but in our proposed problem, information is not shared among customers each other. Moreover, our proposed problem has existing uncertainties in the lower level. Thus, we introduce the common bi-level stochastic linear model as follows:

$$\begin{aligned} \text{Upper level:} \quad & \min F(P^g) = \sum_t C(P^g)_t \\ & \text{s.t.} \quad O_1 P^g + R_1 \leq b_1, \quad P^g \geq 0 \\ \text{Lower level:} \quad & \min f(P^g) = c_2 \hat{P}^g + \Phi(\hat{P}^g, P^g(\xi, \zeta)) \\ & \text{s.t.} \quad O_2 \hat{P}^g + R_2 \leq b_2, \quad P^g \geq 0 \\ & \Phi(\hat{P}^g, P^g(\xi, \zeta)) = \mathbb{E}_{\xi,\zeta}[b(\hat{P}^g, \xi, \zeta)] \\ & \text{s.t.} \quad W_{\xi,\zeta} P^g(\xi, \zeta) = r_{\xi,\zeta} - T_{\xi,\zeta} \hat{P}^g, \quad P^g \geq 0 \end{aligned} \tag{22}$$

We implement this model to our proposed problem, where the lower level represents the customer's model, while the upper level represents the operator's level. Details will be presented in the following subsections.

4.1 | Customer's model: minimizing electrical cost

4.1.1 | Objective function

For each customer $m \in M$, the objective includes all electricity expenditures, such as an electric vehicle, electric appliances, renewable power generation profits (investment fee and maintenance fees are not considered as they are usually at a fixed value) and storage battery degradation fee:

$$\begin{aligned}\min f(P^g) &= \sum_t \left(B_t(P^{g+})_t - U_t(P^{g-})_t\right)\\ &= \sum_t \left(C_t^x + \mathbb{E}[C(P_t^r(\boldsymbol{\xi}) - P_t^f(\boldsymbol{\zeta})) + C_t^v]\right)\end{aligned} \tag{23}$$

where $P^{g+} = P^g$, if $P^g \geq 0$; $P^{g-} = |P^g|$, otherwise.

Generally, the customers' electricity bill is simply the profit of selling electricity to the grid plus the cost of regular use, shown in the first line equation. In this user's objective function, we consider the following parts as electricity costs: battery storage, EV operation and household electrical equipment operation, and the profit part consists of power generated by renewable energy, as shown in the second line of the equation. Due to the randomness of the devices, we implement stochastic programming in the lower level problem through the idea of stochastic linear programming introduced at the beginning of this section.

4.1.2 | Constraints

In the household energy system, in addition to the characteristics of each specific device introduced in Sections 3.2– 3.5, here we add the following general constraints in the home energy system:

$$\begin{aligned}&P^f(\zeta^f) + P^r(\xi^r) + P^v \leq P^{\max}\\ &P^g = P^r(\xi^r) \pm P^v \pm P^x - P^f(\zeta^f)\end{aligned} \tag{24}$$

Here, the two random variables $P^f(\zeta^f)$ and $P^r(\xi^r)$ are the power demand of household common electrical devices and power generated by renewable power generation, respectively. And the variables P^v and P^x are the EV operation and backup storage power exchange, respectively. These constraints indicate that the total household power consumption should not exceed the maximum value of $P^{\max}$, and the power transmission from the grid to the customer should be balanced.

4.2 | Operator's model: minimizing power consumption expenses and power loss

4.2.1 | Objective function

In this work, we use the minimum system loss as the objective function in the distribution system. Some losses, such as investment and maintenance costs, are usually at a fixed rate, so they are excluded from the total system expenditure. We include the power loss and electrical supply in this formulation, given by

$$\begin{aligned}\min F(P^+) &= \sum_n \sum_t (C(L_{n,t}) + C(P_{n,t}^+) + C(P_{n,t}^-))\\ &= \sum_n \sum_t \left(H_t \cdot (L_{n,t}) + U_t \cdot (P_{n,t}^-) - B_t \cdot (P_{n,t}^+)\right)\\ &\forall n \in N\end{aligned} \tag{25}$$

4.2.2 | Constraints

$$P_n = \sum_{m\in M} P_m^g,$$

$$\text{where } P_n^+ = P_n, \text{if } P_n \geq 0; \quad P_n^- = |P_n|, \text{otherwise} \tag{26a}$$

$$\underline{P_{n,t}} \leq P_{n,t} \leq \overline{P_{n,t}}, \quad \underline{V_{n,t}} \leq V_{n,t} \leq \overline{V_{n,t}}, \forall n \in N \tag{26b}$$

Equations (1)–(4). (26c)

In the operator's model, node power [Equation (26a)] can be summed by the house power consumption, followed by the node power limits and node voltage power limits [Equation (26b)]. Adjusting the power that the operator (utility) purchases from customer C^{P^+} not only helps maintain the grid power balance, but also helps achieve optimal operations for the utility companies.

5 | DECENTRALIZED BI-LEVEL STOCHASTIC LINEAR PROGRAMMING

In general, our problem cannot be solved by the standard Stackelberg game model, because customers do not share information with each other to keep their privacy. But this allows us to distribute computing tasks to accelerate the process. In this section, we present a decentralized bi-level stochastic linear programming, in which the operator serves as the upper level, and the customer serves as the lower level.

Note that the proposed problem is in a multi-stage, bi-level and stochastic architecture, which makes this problem very complicated to solve. Therefore, we first propose two methods to reduce the complexity, and the decentralized architecture will be presented after.

5.1 | Problem decomposition

Due to the multi-stage structure of the proposed problem, we first decouple the problem by time, and transfer the problem into a dynamic programming formulation as follows:

$$\begin{aligned}f(P^g) &= \sum_t \left(C_t^x + \mathbb{E}[C(P_t^r(\boldsymbol{\xi}) - P_t^f(\boldsymbol{\zeta})) + C_t^v]\right)\\ &= \left[f(P^g)_{t_1} + \mathbb{E}\left[f(P^g)_{t_2} \cdots + \mathbb{E}\left[f(P^g)_T\right]\right]\right]\end{aligned} \tag{27}$$

For a specific time t, we can reformulate the objective function as follows:

$$\begin{aligned}1 \min \hat{f}(P^g)_t &= f(P^g)_t + \mathbb{E}\left(\hat{f}(P^g)_{t+1}\right)\\ &= C(P^g)_t + \mathbb{E}\left(C(P^g)_{t+1}\right)\\ &= B_t(P^{g+})_t - U_t(P^{g-})_t + \mathbb{E}\left(B_t(P^{g+})_t - U_t(P^{g-})_t\right)\end{aligned} \tag{28}$$

Moreover, we can further decompose the lower level by each device as follows:

$$
\begin{aligned}
5\psi(E_t^v)+ \quad \psi(E_t^x) \quad +\psi(P^r(\xi^r)) \quad +\psi(P^f(\zeta^f)) \quad &= b_1 : \mu^{cp} \\
\psi(E_t^v) \quad &= b_2 : \mu^v \\
\psi(E_t^x) \quad &= b_3 : \mu^x \\
\psi(P^r(\xi^r)) \quad &= b_4 : \mu^r \\
\psi(P^f(\zeta^f)) \quad &= b_5 : \mu^f
\end{aligned} \tag{29}
$$

where function ψ indicates the relations among the devices, and the coupled constraints (μ^{cp}) are shown as follows and we introduce the slack variable π:

$$
\begin{aligned}
&P^f(\zeta^f) + P^r(\xi^r) + P^v + \pi = P^{\max} \\
&P^g = P^r(\xi^r) \pm P^v \pm P^x - P^f(\zeta^f)
\end{aligned} \tag{30}
$$

Therefore, all the variables are bounded and we can decompose the proposed problem to the following format with extreme points set $j \in J$ as follows:

$$
\begin{aligned}
&\min \hat{f}(E^v, E^x, P^r(\xi^r), P^f(\zeta^f)) \\
&= C_t^v\left(\sum_{j\in J^v} \mu_j^v(E_j^v)\right) + C_t^x\left(\sum_{j\in J^x} \mu_j^x(E_j^x)\right) \\
&\quad + C_t^r\left(\sum_{j\in J^r} \mu_j^r(P^r(\xi^r))\right) + C_t^f\left(\sum_{j\in J^f} \mu_j^f(P^f(\zeta^f))\right)
\end{aligned} \tag{31}
$$

Then, we can find optimal solutions for each variable which we define as $E^{v\circ}$, $E^{x\circ}$, $P^r(\xi^r)^\circ$ and $P^f(\zeta^f)^\circ$, and we use subscripts $1, 2, \ldots, j$ to define the number of the optimal solution of each variable as follows:

$$
\begin{gathered}
E^{v\circ} = \mu_1^v E^{v\circ}{}_1 + \mu_2^v E^{v\circ}{}_2 + \cdots \mu_j^v E^{v\circ}{}_j \\
\mu_1^v + \mu_2^v + \cdots \mu_j^v = 1, \quad \forall j \in J^v
\end{gathered} \tag{32}
$$

$$
\begin{gathered}
E^{x\circ} = \mu_1^x E^{x\circ}{}_1 + \mu_2^x E^{x\circ}{}_2 + \cdots \mu_j^x E^{x\circ}{}_j \\
\mu_1^x + \mu_2^x + \cdots \mu_j^x = 1, \quad \forall j \in J^x
\end{gathered} \tag{33}
$$

$$
\begin{gathered}
P^r(\xi^r)^\circ = \mu_1^r P^r(\xi^r)^\circ{}_1 + \mu_2^r P^r(\xi^r)^\circ{}_2 + \cdots \mu_j^r P^r(\xi^r)^\circ{}_j \\
\mu_1^r + \mu_2^r + \cdots \mu_j^r = 1, \quad \forall j \in J^r
\end{gathered} \tag{34}
$$

$$
\begin{gathered}
P^f(\zeta^f)^\circ = \mu_1^f P^f(\zeta^f)^\circ{}_1 + \mu_2^f P^f(\zeta^f)^\circ{}_2 + \cdots \mu_j^f P^f(\zeta^f)^\circ{}_j \\
\mu_1^f + \mu_2^f + \cdots \mu_j^f = 1. \quad \forall j \in J^f
\end{gathered} \tag{35}
$$

5.2 | Scenario reduction

Since we defined the random distribution of household power demand, and renewable power generation, the scenario set ($\mathbb{R}^r \times \mathbb{R}^f$) could be very large in most cases. Therefore, we can combine some similar scenarios to keep the random set within a computationally tractable range.

For these two random variables, we first redistribute them by the amount of power, as follows:

$$
\begin{aligned}
\zeta_{m,l_f,t}^f &= \sum_{k_f} \zeta_{m,k_f,t}^f, \quad \forall P_{m,l_f,t}^f = P_{m,k_f,t}^f \\
\xi_{m,l_r,t}^r &= \sum_{k_r} \xi_{m,k_r,t}^r, \quad \forall P_{m,l_r,t}^r = P_{m,k_r,t}^r
\end{aligned} \tag{36}
$$

where l represents the power level after the probability distribution is redistributed without duplication. Then, we can decide the accuracy level of the simulation and combine the scenarios to a limited number q as follows:

$$
\begin{aligned}
P_{m,l_f,t}^f(q_f) &= \frac{\max\left(P_{m,l_f,t}^f\right)}{q_f}, \ \forall q_f = 1, 2, \ldots, \mathbb{N}_{l_f} \\
P_{m,l_r,t}^r(q_r) &= \frac{\max\left(P_{m,l_r,t}^r\right)}{q_r}, \ \forall q_r = 1, 2, \ldots, \mathbb{N}_{l_r}
\end{aligned} \tag{37}
$$

Here, the larger the number q, the higher the accuracy of the new distribution allocation. Thus, we can finally achieve the new distribution of the two variables by

$$
\zeta_{m,l_f,t}^f(q_f) = \sum_{l_f} \zeta_{m,l_f,t}^f, \quad \xi_{m,l_r,t}^r(q_r) = \sum_{l_r} \xi_{m,l_r,t}^r \tag{38}
$$

5.3 | Decentralized architecture

The main steps of the proposed optimal control algorithm are described as follows:

1. At the upper level, the operator publishes power limits through power flow analysis and issues different electricity tariffs for different purposes.
2. Each customer can calculate their own minimum electricity cost $\min f(P^g)$ for daily appliances scheduling based on the home energy management system. For privacy reasons, customers can calculate their own expenses individually, which is why this step can be decentralized computing, and customers do not require to share information with each other.
3. Operators at the upper level controller can collect data and information (such as the amount of electricity exchanged by customers from the grid) from all the lower level customers. Based on the information, the operator can decide the next control policy, such as energy obtained from the customers, and then evaluate the cost function (25).

ALGORITHM 1 Decentralized Stochastic Optimization

Utility input: $H_t, U_t, B_t, \underline{P_{n,t}}, \overline{P_{n,t}}, \underline{V_{n,t}}, \overline{V_{n,t}}$
for $n = 1 : N$ **do**
  Utility company decides the amount of power sold from customer to the grid, considering the minimum power loss.
  for customer $1 : M$ **do**
    Assign customer solve their own electricity cost by linear programming to obtain the optimal electricity cost appliances usage schedule.
  end for
end for
Customer input: appliance usage power and probability, EV and battery storage-related properties.
for $t = 1 : T$ **do**
  Multiple stage optimization problem
end for
Until the stopping criterion is satisfied
Each customer can achieve the optimal electricity cost

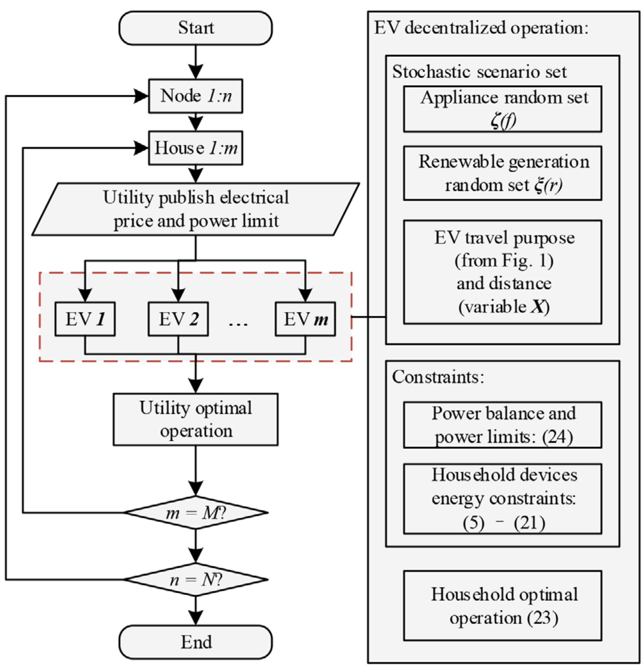

FIGURE 3 Flowchart of the proposed decentralized process

4. Update all equipment status and forecast data for renewable power generation in the smart grid.

We elaborate on the details in Algorithm 1 and the flowchart in Figure 3.

6 | CASE STUDY

In order to evaluate the performance of the proposed approach under the randomness of household demand, renewable energy generation and EV uncertain driving patterns, a case study was conducted in this section. The simulation was performed on a Windows desktop with an Intel Core i7-4790 CPU at 3.60 GHz with 16 GB of random access memory (four physical cores and eight logical cores). It should be noted that in order to implement the proposed EV decentralized operation, we use OpenMP parallel computing to serve each core as an individual EV.

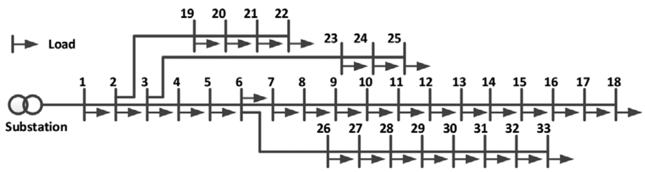

FIGURE 4 One-line diagram of IEEE 33-bus test distribution system

TABLE 1 Electrical characteristics of electric vehicle

EV battery capacity	40 kWh
Full charged battery range	242 km
EV battery efficiency	18.55 kWh/100 km
Average annual driving distance	20,000 km
Average daily distance	Random from Figure 2
Min and max SOC for healthy battery	20%–80%
Battery lift span	15 (years)

6.1 | Simulation set-up

The proposed decentralized operation scheme was tested on the IEEE 33-bus distribution system, and the system data are provided in [29], where the total active and reactive power loads on the system are 3715 kW and 2300 kVar, respectively. The system's one-line diagram is shown in Figure 4.

In this simulation, several categories of typical household appliances are considered, whose characteristics can be found in [30]. There are in total 21 kinds of electrical appliances, and 4132 scenarios of power demand $\xi^{f}_{m,l_f,t}$ considered. The range is from 0 W (all appliances are turned off) to 21,725 W (all appliances are turned on). For the PV generation, there are 21 scenarios of power generated $\xi^{r}_{m,l_r,t}$. After scenario reduction technique, there are in total 55 scenarios. Since the EV plays the role of decentralized computing platform, different EV models are not considered in this work. The parameters in this simulation are based on the average values of parameters of popular EV models (such as BMW i3, Ford Focus, Hyundai IONIQ, Nissan Leaf, and Tesla Model S). The parameters can be found in [31], and the average values implemented in the simulation are shown in Table 1.

Moreover, similar to the purpose of the EV parameters, we applied the average values of current popular household energy storage models (such as Tesla, Nissan, LG Chem and Mercedes-Benz) to simulate, with the battery capacity being 10 kWh. This

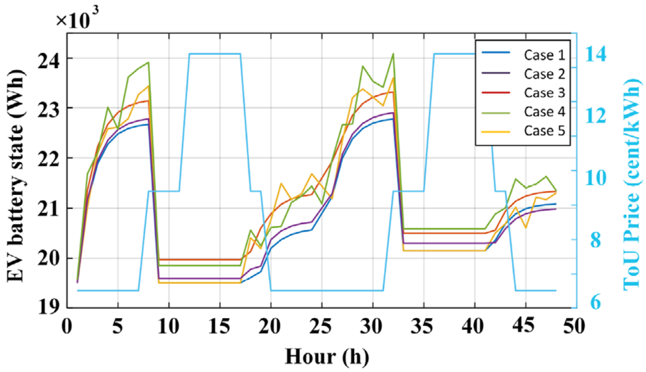

FIGURE 5 EV battery operation status

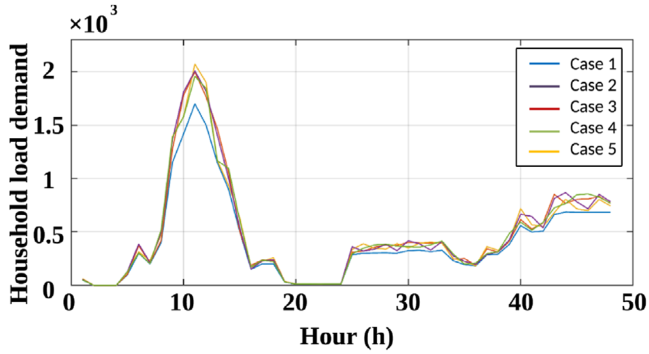

FIGURE 6 Household load demand

system was implemented for a finite time horizon of 48 h in this study, and the time step is set to be 1 h.

Several cases are presented in this simulation to compare with our proposed decentralized scheme.

Case 1. The proposed stochastic programming, which includes 252 scenarios for hourly house load demand and renewable power generation.

Case 2. The maximum probability scenario [32], which means that the scenario corresponding to the maximum probability will be selected for the process.

Case 3. The mean value scenario [33], which is similar to Case 2, but based on the average value of the random scenario.

Case 4. Monte–Carlo randomly selected scenario [34], through which several scenarios will be selected randomly to the process.

Case 5. Worst-case scenario [35], which is based on the highest household energy demand through the time span.

6.2 | Simulation results

In this section, we analyze household energy management and utility optimal operation, respectively.

6.2.1 | Household energy management

With the parameters and datasets introduced above, we first analyzed the stochastic household energy management. The optimal EV energy schedule is shown in Figure 5. The green line indicates the Time of Use (ToU) price in Ontario, Canada. The on-peak price is 13.4 ¢/kWh, mid-peak price is 9.4 ¢/kWh and the off-peak price is 6.5 ¢/kWh. Due to the high randomness in this simulation, in order to make a fair comparison, we used the fixed variable method to model the randomness related to EV travels, including travel start time and travel distance. In this simulation, all cases were selected for education purposes during the first 24 h, and commute purpose was selected over the last 24 h to make all scenarios fair.

As we can see, the EV starts operation when it arrives at home, and the battery energy status shows that the battery is being charged during off-peak hours. Because of the different purposes and driving distances of the EV, the battery discharges when it leaves the house. Moreover, the charging rate varies depending on the household load demand. For example, the rate at night is low and becomes slightly higher in the morning. Specifically, the trends of the EV battery status in all cases indicate that EVs are operating when they return home, except that they leave the house between 9 AM and 5 PM, and between 33 and 41 (the next day from 9 AM to 7 PM). For the consecutive night from time period 17 to 33 (7 PM on the first day to 9 AM the next day), the EV trend shows that it is charging, but the trend becomes different as the load demand changes. In addition, our proposed scheme Case 1 is very close to Case 2, which is because, in the stochastic programming process, all scenarios were evaluated for optimization, while a larger probability may have a more significant impact on the process. Case 3 shows a smoothing trend compared to Case 4, and the total home electric costs are \$4.02, \$4.10, \$4.26 and \$4.44, respectively.

In addition, the household load demand is shown in Figure 6. We can see that in the first 24 h, the load demand increases during the day and decreases at night, depending on the family with two or more children. In the next 24 h, due to high electricity prices, the load demand first drops in the morning and afternoon, while the load increases at night. This is because the family consists of multiple people but no dependent children. In addition, compared with the case, our Case 1 shows a relatively flatter trend than other cases, which shows a better performance than other cases.

6.2.2 | Utility optimal operation

In the home energy management system, our proposed approach Case 1 shows a slight advantage compared to another method. However, the difference between the system operation costs of utility becomes larger, according to the utility expense convergence results shown in Figure 7. As we can see, all cases converged during the first 30 iterations. Our proposed approach shows the fastest convergence with the lowest operating expense. In this figure, compared to Case 2, the trend for

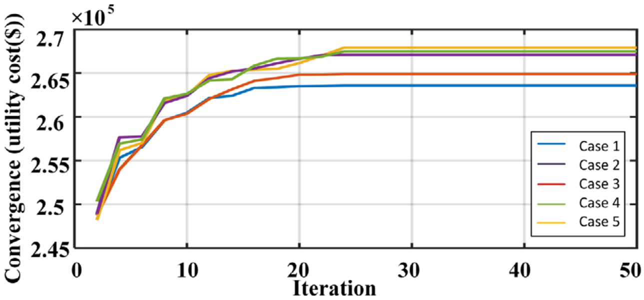

FIGURE 7 Utility cost ($)

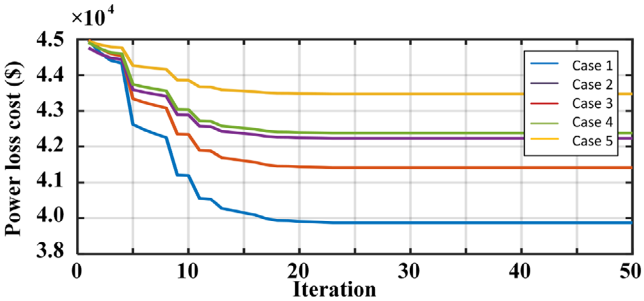

FIGURE 8 Power loss ($)

Case 3 is closer to Case 1, which is the opposite of home EV operation. This suggests that when there is a long-term dataset or a large dataset available, the maximum probability scenarios and mean value scenario seem to be well optimized, but for a single realization problem, we need to analyze from the bottom, such as analyzing each customer's habits. Moreover, the power loss shown in Figure 8 is more pronounced to show the advantage of our proposed method.

The execution time for all the cases is shown in Table 2. The results indicate that for residents, due to the limited number of special scenarios, the execution time of special cases (Cases 2–5) is faster than our proposed method. And generally, for utility companies with large datasets, the average value scenario case (Case 3) is usually used, which makes sense comparing the results for utility cost and power loss, where the average case has the closest performance of our proposed algorithm. In addition, for other cases (cases 2, 4, 5) are usually implemented in traditional optimization, so they are not suitable for actual cases. For our proposed algorithm, the performance of execution time may not be as good as other cases, but through technology development, due to the decentralization of the proposed algorithm, it is feasible to perform complex calculations using existing equipment such as EV or smartphones.

TABLE 2 Execution time

Case number	Execution time	Case number	Execution time
Case 1 (4 cores)	66.45 s	Case 3	6.22 s
Case 1 (1 cores)	278.32 s	Case 4	5.81 s
Case 2	5.64 s	Case 5	6.04 s

7 | CONCLUSION

Stochastic energy management is of considerable significance in distribution systems. This paper developed a household stochastic energy management model that consists of electrical devices, renewable energy generation, energy storage systems and EVs. In addition to the typical expense costs in the objective function, degradation cost for energy storage and EV is also considered in our model. The uncertainty of solar power generation is captured by a stochastic probability model. Furthermore, to protect customer privacy, we present a decentralized bi-level stochastic linear programming model, in which the operator serves as the upper level, and the customer serves as the lower level. To reduce the computation complexity, problem decomposition and scenario reduction techniques are applied to improve efficiency. The proposed method has been analyzed through a case study, and the simulation results show the effectiveness and reliability. Moreover, the comparison with the approach with specific cases validates the advantages of the proposed method, which is more applicable in practice in the future smart grid. Uncertainties due to real-time pricing schemes, parking lot or charging station availability and renewable energy generation farm can be explored in future extensions of this work.

NOMENCLATURE

Superscript

- c Charging process
- d Discharging process
- f Households
- g Power grid
- r Renewable power generation
- u EV start operation time
- v EV operation
- x Energy storage
- z EV stop operation time

Variables

- ξ Household customers' activities distribution
- δ_1, δ_2 Battery degradation linear fit coefficient
- η Efficiency of different components
- $\mathcal{L}$ Power loss
- μ Lagrange multiplier
- ξ^r Probability distribution of renewable power generation
- ζ^f Probability distribution of house load consumption
- B Electrical price for customer purchase from utility
- C Cost
- D Battery degradation
- E Energy
- $G()$ Price-sensitive function
- H Electrical price for electricity wholesale price
- $h()$ Probability distribution function
- I Line current phasor
- I_β Solar irradiance with PV array inclination angle β
- O, R, b Bi-level model linear variables

P	Real power
p	Probability
Q	Reactive power
S	Complex power flow
U	Electrical price for customer sell to utility
V	Line voltage phasor
w	PV array area
X	EV travel distance
Y	Admittance
y	Battery life span
Z	Storage capacity
σ	Coefficient of household probability distribution

Sets and individuals

A, a	House appliances $a \in A$
J, j	Extreme points $k \in K$
K, k	Scenarios $k \in K$
M, m	Households $m \in M$
N, n	Bus nodes $n \in N$
T, t	Time slots $t \in T$

Abbreviations

EV	Electric vehicle
PV	Photovoltaics
SOC	State of charge
ToU	Time of use

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ORCID

Yue Wang https://orcid.org/0000-0003-2060-8497
Venkata Dinavahi https://orcid.org/0000-0001-7438-9547

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