Purchase' Portfolio Optimization of Power Supply Company with Distributed PV Considering EVs

Hui Ren, Aiwei Zhang, Kangping Li
Department of Electrical Engineering
North China Electric Power University
Baoding 071003, China
hren@ncepu.edu.cn, zhangaiwei0517@outlook.com

Yahong Li
State Grid Yulin Power Supply Company
Yulin 719000, China
liyahong90s@outlook.com

Fei Wang
State Key Laboratory of Alternate Electrical Power System with Renewable Energy Sources (North China Electric Power University), Baoding 071003, China; also with Department of Electrical Engineering, North China Electric Power University, Baoding 071003, China; also with Hebei Key Laboratory of Distributed Energy Storage and Micro-grid (North China Electric Power University)
Baoding 071003, China
feiwang@ncepu.edu.cn

Miadreza Shafie-khah
C-MAST, University of Beira Interior
6201-001 Covilhã, Portugal
miadreza@ubi.pt

João P. S. Catalão
INESC TEC and FEUP, 4200-465 Porto, Portugal; also with C-MAST/UBI, 6201-001 Covilhã, Portugal; also with INESC-ID, IST-UL
1049-001 Lisbon, Portugal
catalao@ubi.pt

Abstract—In recent years, with the vigorous development of the new energy industry in the world, distributed photovoltaics (PV) have strongly penetrated the international energy markets at exponential growth rates, and a large number of electric vehicles (EVs) have been used mainly driven by policies. The use of EVs and distributed PV would lead to an increase in load uncertainty. Hence, a new day-ahead portfolio optimization model for a power supply company with distributed PV considering EVs was developed. The model contains risks depending on market price fluctuation and load uncertainty caused by EVs load, conventional load and distributed PV's output, considering the expected cost of errors, and helping to determine an optimal quantity of power to be obtained from distributed PV's output and different electricity markets. This paper analyses the efficient frontier of conditional value-at-risk (CVaR) and the influence of different EVs market penetration levels and distributed PV's output on the portfolio strategy.

***Index Terms*—CVaR, distributed PV, EVs load, market penetration level, purchase' portfolio optimization.**

LIST OF SYMBOLS

$SoC(t_1)$	SoC (state of charge) of a battery at the beginning of a trip
$SoC(t_2)$	SoC of a battery at the end of a trip
t_1, t_2	start-time and end-time of the trip
d	the distance traveled in between t_1 and t_2
d_R	an EV's maximum mileage
$p_{s,t}$	Probability of scenario s at time moment t
$\pi_{s,t}$	Profit obtained under scenario s in period t
$z_{s,t}$	Scenario s variable used to compute CVaR
Φ_t	Value at risk at time moment t
γ	Risk aversion coefficient
α	Confidence level
$e_{c,t}$, $e_{da,t}$	Electricity bought through forward contract and day-ahead market at time period t
$E_{pv,t}$	The expected value of the PV's output under the installed capacity of time period t
x_t	the ratio of the amount of PV power purchased to $E_{pv,t}$
P_d	Tariff at which Power Supply Company provides power to consumers
P_c, $P_{das,t}$	Electricity price for forward contract and day-ahead market at time period t, respectively
P_{dc}	Benchmarking electricity price for desulfurization coal-fired units
$\Delta\pi_{\delta,t}$	The all expected cost of errors at time period t
$\Delta\pi_{Dc,t}$, $\Delta\pi_{pv,t}$, $\Delta\pi_{Dev,t}$	The expected cost of errors caused by conventional load, PV's output and EVs load at time period t
$(D_{fci,t}, P_{fDci,t})$	PDF of the conventional load at time period t
$(D_{fevj,t}, P_{fevj,t})$	PDF of the EVs load at time period t
$(D_{fpvk,t}, P_{fpvk,t})$	PDF of the distributed PV's output at time period t
$P_{\delta+}$, $P_{\delta-}$	Cost of the positive and negative load errors.
$D_{c,t}$, $D_{ev,t}$	The expected value of the conventional load and the EVs load at time period t, respectively
$e_{cmin,t}$, $e_{cmax,t}$	the minimum and maximum limits of the long-term contract sales volume

I. INTRODUCTION

In recent years, the global energy production and consumption continues to grow, and fossil energy is extensively exploited and utilized resulting in resource constraints, environmental pollution, climate change and many other global problems, which poses a serious threat to human survival and development.

Promoting the use of new energy is the inevitable trend of global energy development in the future and the fundamental way to cope with severe challenges of energy constraints and environmental constraints. Under these circumstances, electric vehicles (EVs) and distributed photovoltaics (PV) have made sustainable progress and obtained significant market volume. In 2015, the global PV market is growing strongly, and new installed capacity is expected to exceed 50GW, which is a 16.3% year-on-year growth, and the cumulative PV capacity is more than 230GW. Estimation shows that, by 2020, 30% of the electricity of the world will come from green energy, and by 2040, 75% of light vehicles will be powered by electricity. More and more EVs and distributed PV will be put into use, which would lead to an increase in load uncertainty, and then bring great challenges to the grid planning, operation, the safe operation of the electricity market.

In recent years, many scholars have conducted studies on the impact of EVs and distributed PV on the distribution system, distribution transformer aging, and others [1]-[5]. However, research on the impact of EVs and distributed PV on purchase' portfolio optimization of power supply company is still under highlighted. Fluctuation of PV's output and randomness of EV load would have a great impact on load uncertainty, and thus power supply company may face more serious volume risk. For example, the impact on the demand response application and the baseline estimation of incentive-based demand response [6]-[9]. Even though these influences can be mitigated somehow such as by accurate solar PV power forecasting [10-15], the researches on the inner mechanism related risk evaluation and management problems still need to be addressed.

The risk measurement tools, such as Value at Risk (VaR), are commonly used to describe the impact of the different power purchase portfolios of power supply company on operating cost and risk [16]-[18]. Although VaR is insensitive to extreme risks, the discrete distribution of VaR may cause failures in optimization problems [19]. Conditional value at risk (CVaR) has since been adopted [20]-[22] for improvement. Taking CVaR as the risk indicator, a medium-term portfolio optimization model considering interruptible load market and the DG market is established [20]. A portfolio optimization model for a power producer considering a scenario tree of locational electricity prices and risk management with CVaR is presented [21]. CVaR is applied in the dynamical scheduling optimization model for virtual power plant connected with wind-photovoltaic-energy storage system with uncertainties and demand response [22]. Therefore, in this paper, CVaR is utilized to quantify the risk and integrate the risk management problem into purchase's portfolio optimization including price and load uncertainty.

The main contribution of this paper is to provide a new day-ahead portfolio optimization model for power supply company based on CVaR, which considers the randomness in price and load uncertainty caused by conventional load, EVs load and distributed PV's output. This paper aims at minimizing the risk faced by the company under the condition of ensuring a certain profit, and analysing in deep the rising space for profit and potential risk value caused by EVs load and distributed PV's output.

The rest of the paper is organized as following: Section II introduces the CVaR theory. Section III proposes a probability density prediction model of conventional load, probabilistic model of distributed PV's output, and EVs charging model based on driving patterns and a purchase' portfolio optimization model. Case study to verify the proposed model and analysis of the simulation results are given in section IV. Section V concludes the paper.

II. CVaR Theory

The definition of CVaR adopted in this paper is the conditional mean of the profit below VaR, which is CVaR=$E[\pi|\pi\leq\text{VaR}]$, where π is profit, α is the confidence level and VaR is defined as the α quantile of π: VaR=$\max\{x: P(\pi\leq x)\leq 1-\alpha\}$. For instance, if α=0.95 then CVaR is the expected value of profit given that profit is below its 5% quantile. The concept of CVaR is depicted in Fig. 1. CVaR has sub-additive property, and can measure tail risk. These properties make CVaR applicable for portfolio diversification. The CVaR in the optimization model is modelled [23], assuming there is a finite set of profit scenarios $\{\pi_s\}_{s=1}^{S}$ with probabilities $\{P_s\}_{s=1}^{S}$. CVaR can be transformed into the following linear optimization:

$$\max \varphi - \frac{1}{1-\alpha}\sum_{s=1}^{S} P_s z_s \tag{1}$$

$$\text{s.t.} \quad z_s \geq \varphi - \pi_s \quad \forall s = 1,\cdots,S \tag{2}$$

$$z_s \geq 0 \quad \forall s = 1,\cdots,S \tag{3}$$

III. Models

Probability density prediction model of conventional load, probabilistic model of distributed PV's output, EVs charging model and the new day-ahead portfolio optimization model with consideration of distributed PV and EVs are presented in this section.

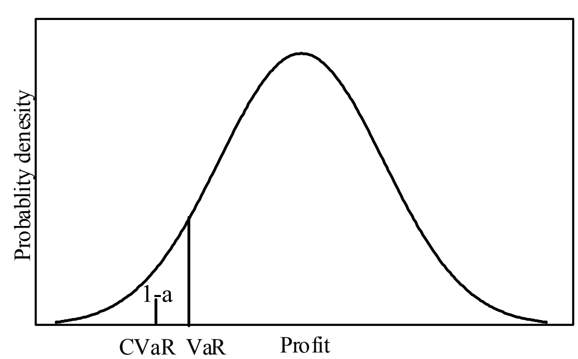


Fig.1. Concept of conditional value at risk

A. Probability density prediction model of conventional load

The probability density prediction of conventional load is carried out based on nonparametric kernel density estimation method. It has higher accuracy and better robustness because the expression of the density function is derived from the existing sample data without the limitation of the distribution.

The probability density function is given in (4):

$$f\left(D_{c,t}\right) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{D_{c,t} - D_{c,t}(i)}{h}\right) \tag{4}$$

where n is the sample size of conventional load data. h is the bandwidth, which can be calculated by rule of thumb (ROT). $K(\cdot)$ is a kernel function. In this paper, we choose Gaussian function as kernel function.

B. Probability model of distributed PV's output

The output of photovoltaic cells varies with the solar irradiance. In a certain period of time, the solar irradiance follows the Beta distribution, thus, the random output of PV can be derived accordingly [24].

The probability density function is described by (5):

$$f_P(P) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)}\left(\frac{P}{P_{max}}\right)^{a-1}\left(1-\frac{P}{P_{max}}\right)^{b-1} \tag{5}$$

where P_{max} is the maximum output of PV; $\Gamma(\cdot)$ is Gamma function; a and b are parameters of the Beta distribution.

C. EVs charging model based on driving patterns

1) The models for driving patterns of EVs:

Statistics on the driving behavior of commuter in a residential area in Beijing includes trip chain category, start-time of commuters' trip, end-time of the trip, and travel distance. Trip chain is defined as home to someplace to home (h2h).

In the study, the case of Nissan Altra EV is used as example, in which, battery capacity is 29.07 kWh and the highest mileage is 130 km. In order to prevent a so-called range anxiety, the subset of potential users are chosen according to the maximum range of 110 km so that at least about 10% of energy would be left after an h2h trip.

According to the statistical results, commuter trip situation is mainly divided into two types: single h2h trip and double h2h trip. The former refers to complete an h2h trip in one day and occupies 70% of the users, while the latter refers to complete two h2h trips in one day and occupies 28% of the users. The rest situations, which have three or more h2h trips, is ignored.

Modeling of single h2h trip requires 3 variables: start-time (T_s^s), end-time of the h2h trip (T_s^b), and travel distance (D_s), whereas a double h2h trip needs six variables: start-time, end-time, and travel distance of the first h2h trip (T_{d1}^s, T_{d1}^b, D_{d1}) and the second h2h trip (T_{d2}^s, T_{d2}^b, D_{d2}).

According to the statistical data, the probability distribution curves of the start-time (T_s^s, T_{d1}^s, T_{d2}^s), travel end-time (T_s^b, T_{d1}^b, T_{d2}^b), travel distance (D_s, D_{d1}, D_{d2}) of single and double h2h trip are shown in Fig. 2. Then, according to marginal distributions of single and double h2h trip and the Copula function, the single h2h trip joint probability distribution F_s and the double h2h trip joint distribution F_d, which characterize the EVs driving patterns, are obtained.

2) Battery charging model:

According to the above-mentioned start-time distribution, end-time distribution, and travel distance distribution, the possible charging time interval of the commuter and the energy value to be charged can be obtained.

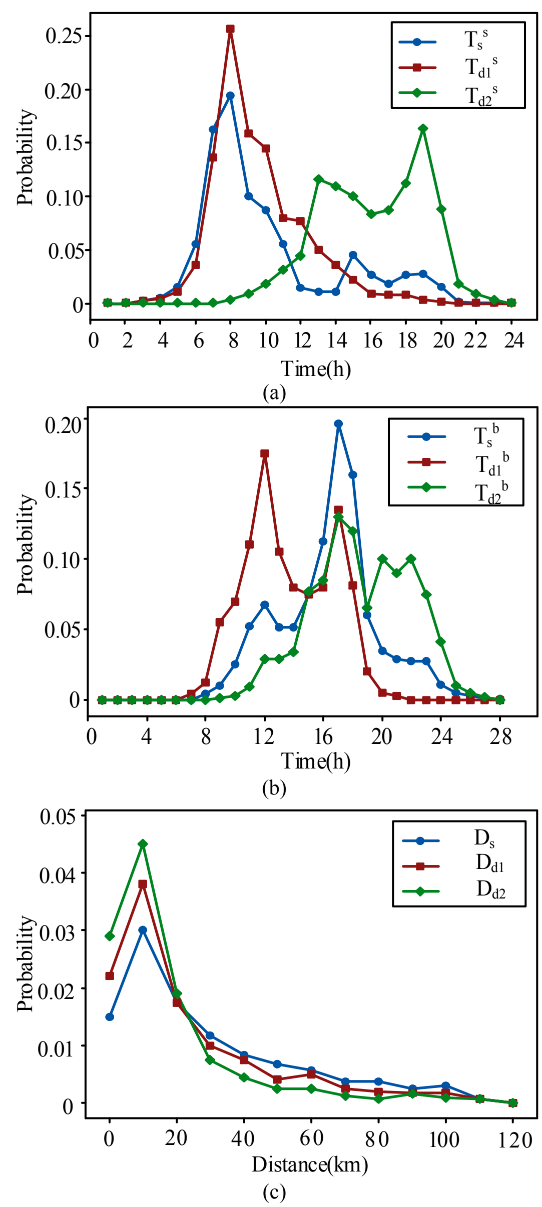


Fig.2. Distributions of the start-time, travel end time, travel distance.

This paper only considers the situation where the commuter is charged at home and assumes that the commuter charges the EVs when *SoC* (state of charge) of the EV battery is less than 50% or when the battery is insufficient to survive the next trip. The charge energy can be calculated according to the travel distance of each time and the initial *SoC* of the battery. Between *SoC* at the beginning of charging and the travel distance since the last charging time is a linear relationship, as in [25]. The formula for the initial *SoC* is expressed as (6)

$$\mathrm{SoC}(t_2) = \left(\frac{\mathrm{SoC}(t_1)}{100} - \frac{d}{d_R}\right) \times 100\% \tag{6}$$

where $SoC(t_1)$ and $SoC(t_2)$ are *SoC* of EV's battery at the start and the end of a trip, respectively; d is the distance traveled between time t_1 and t_2; d_R is an EV's maximum mileage. If the commuter travels when the EV is not fully charged after the last trip, $SoC(t_1)$ may be less than 100% at the beginning of the trip, so that the initial *SoC* depends both on the distance traveled by last charging and on the charging history.

D. The day-ahead portfolio optimization model for Power Supply Company with distributed PV considering EVs

In this paper, electricity purchased by power supply company includes three parts: forward contract, day-ahead market and distributed PV. Forward contract does not provide a fixed contract volume, but the minimum and maximum limits, and it is considered that there is no penalty for the buyer as long as the purchase is within the limits. The rest of demand is supported by day-ahead market and distributed PV. Distributed PV can be regarded as a contract: the power supply company purchases electricity from DG owners at benchmarking price of desulfurization coal-fired units and provides electricity to consumers at a regulated tariff. The purchase plan is made every hour (24 blocks of a day) in the portfolio optimization model.

The day-ahead portfolio optimization model considers risks depending on market price fluctuation, load uncertainty caused by EVs load, conventional load, and distributed PV's output, as well as expected cost of errors. The market price is subject to normal distribution, and the forward contract price is regarded as constant.

The portfolio optimization problem is expressed as follows:

$$\max \sum_{s=1}^{S} p_{s,t}\,\pi_{s,t} + \gamma(\varphi_t - \frac{1}{1-\alpha}\sum_{s=1}^{S} p_{s,t} z_{s,t}) \tag{7}$$

$$z_{s,t} \geq \varphi - \pi_{s,t} \quad \forall\, s = 1, \cdots, S \tag{8}$$

$$z_{s,t} \geq 0 \quad \forall\, s = 1, \cdots, S \tag{9}$$

$$\begin{aligned}\pi_{s,t} = &\left(e_{c,t} + e_{da,t} + E_{pv,t}x_t\right)P_d - P_c e_{c,t} \\ &-P_{das,t}e_{da,t} - P_{dc}E_{pv,t}x_t - \Delta\pi_{\delta,t}\end{aligned} \tag{10}$$

$$\Delta\pi_{\delta,t} = \Delta\pi_{Dc,t} + \Delta\pi_{Dev,t} + \Delta\pi_{pv,t} \tag{11}$$

$$\begin{aligned}\Delta\pi_{Dc,t} = \sum_{i=1}^{I} P_{fD_{ci,t}} \Big(&max\left(\left(D_{fci,t} - D_{c,t}\right), 0\right) P_{\delta+} \\ &+ max\left(\left(D_{c,t} - D_{fci,t}\right), 0\right) P_{\delta-}\Big)\end{aligned} \tag{12}$$

$$\begin{aligned}\Delta\pi_{Dev,t} = \sum_{j=1}^{J} P_{fevj,t} \Big(&max\left(\left(D_{fevj,t} - D_{ev,t}\right), 0\right) P_{\delta+} \\ &+ max\left(\left(D_{ev,t} - D_{fevj,t}\right), 0\right) P_{\delta-}\Big)\end{aligned} \tag{13}$$

$$\begin{aligned}\Delta\pi_{pv,t} = \sum_{j=1}^{J} P_{fpvk,t} \Big(&max\Big(\big(E_{fpvk,t}x_t \\ &- E_{pv,t}x_t\big), 0\Big) P_{\delta+} \\ &+ max\Big(\big(E_{pv,t}x_t \\ &- E_{fpvk,t}x_t\big), 0\Big) P_{\delta-}\Big)\end{aligned} \tag{14}$$

$$e_{c,t} + e_{da,t} = D_{c,t} + D_{ev,t} + E_{pv,t}x_t \tag{15}$$

$$e_{cmin,t} \leq e_{c,t} \leq e_{cmax,t} \tag{16}$$

$$0 \leq x_t \leq 1 \tag{17}$$

$$\mathrm{t} \in (0,23) \tag{18}$$

Equation (7) for the objective function consists of expected profit and CVaR, which are connected by the risk aversion coefficient γ. The CVaR consists of the second items of (7), (8), and (9). Equation (10) is the total profit of the power supply company at time period t under scenario s, which includes the expected cost of errors. From (11), it is can be seen that the sources of the expected cost of errors contain three parts: conventional load, EVs load, and PV's output. Equation (12), (13), and (14) represent the expected cost of errors, consisting of positive and negative deviations caused by conventional load, EVs load, and distributed PV's output respectively. Equation (15) models demand-supply balance. The minimum and maximum limits of the long-term contract sales volume are presented in (16). Equation (17) represents the bounds of the ratio of the power purchased of PV to the total PV's output. Equation (18) indicates that a purchase plan is made every hour i.e., 24 blocks of a day.

IV. Case Study

A. Study Case

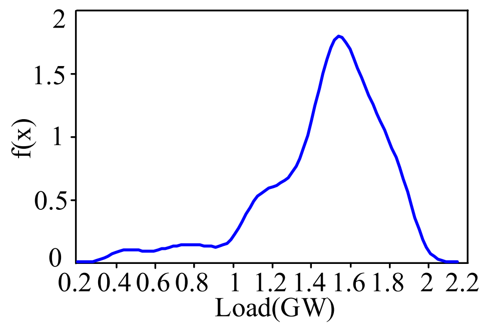
The paper takes a power supply company in Beijing as an example, which supplies electricity for about 10% area of Beijing. The peak load of this region is approximately 2GW, while the total installed capacity of distributed PV is about 23MW, and the car park is around 600,000. 60,000 EVs is corresponded to approximately 10% EVs market penetration in 2017 in the region.

The parameters related to the proposed model for power supply company are given in Table I. MATLAB optimization toolbox Yalmip is used to solve the model.

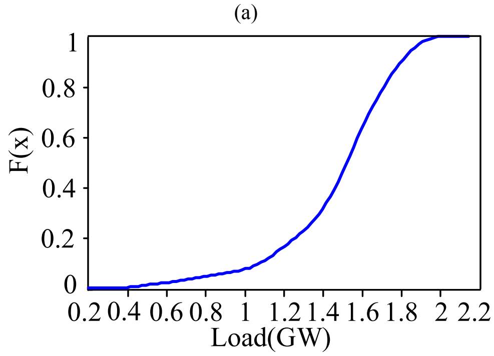
TABLE I
THE PARAMETERS RELATED TO THE MODEL

Parameters	P_d	P_c	$P_{\delta+}$	$P_{\delta-}$	$P_{da,t}$
Value(yuan/MWh)	490	450	100	50	N(430,46)

Taking the conventional load data and the solar irradiance data from July 2016 to July 2017 in Beijing as an example, according to the time period of each day, data of 24 groups with 365 data for each group are formed. The conventional load data for each group is used to estimate the non-parametric kernel density of the conventional load at correspondent period of the next day. In this section, we take the 19th interval as an example, and the probability density distribution and the cumulative distribution are shown in Fig.3.



(a)



(b)

Fig.3. The probability density distribution and the cumulative distribution of the conventional load at the 19th interval.

The hourly average solar irradiance is calculated. For simplicity, we assume that the solar irradiance is considered to be subject to the same Beta distribution during the same period of time each day. The mean μ and the standard deviation σ of solar irradiance of each time period is figured out, and then a and b can be obtained by (19) and (20), respectively.

$$\alpha = \mu\left[\frac{\mu(1-\mu)}{\sigma^2} - 1\right] \tag{19}$$

$$b = (1-\mu)\left[\frac{\mu(1-\mu)}{\sigma^2} - 1\right] \tag{20}$$

The maximum output of distributed PV's at each period is taken as the maximum output P_m of the time period. The corresponding parameters of the distributed PV are shown in Table II. The simulation steps of EVs charging load are summarized as follows:

-Firstly, the multivariate joint distribution functions of single h2h trip F_s and double h2h trip F_d can be created using the copula function and the marginal distributions, respectively;

-Secondly, the simulations are performed for two consecutive days. On the first day, it is assumed that an EV is started with a fully charged battery, and the *SoC* of the EV every time at the end of the trip is calculated using (6). If the state of charge is in line with the charging conditions, the electric vehicle will be charged, otherwise the *SoC* will be considered to be the initial *SoC* of the next trip;

-Thirdly, results of the second day are used to calculate the EVs load. If the simulation procedure for an EV is made is dependent on whether the driver will commute during the first day and the second day. The driving patterns are simulated using distributions F_s and F_d based on the probability of occurrence of their respective h2h trips.

-Finally, the Nissan-Altra battery charging curve [15] is applied to get the hourly electricity demand of each EV. The simulation is run for each EV, and the individual hourly power demands are added up. The simulation procedure is run 100 times to show the uncertainty in the EVs load. The uncertainty in the EVs load and EVs load with different penetration levels can be observed in Fig. 4. From Fig. 4, with the increase in penetration, EVs load and its randomness increase.

TABLE II
THE CORRESPONDING PARAMETERS OF DISTRIBUTED PV

time	a	b	P_m(MW)
6	0.443	1.137	0.107
7	0.538	1.287	2.559
8	0.862	1.947	7.670
9	1.862	1.578	11.454
10	1.889	1.477	14.433
11	1.999	1.299	16.536
12	2.034	1.251	18.259
13	1.886	1.141	18.216
14	1.906	1.141	18.051
15	2.119	1.474	16.311
16	2.016	1.507	13.433
17	1.884	1.732	9.610
18	1.537	1.654	4.670
19	0.546	1.378	1.725
20	0.413	1.237	0.022

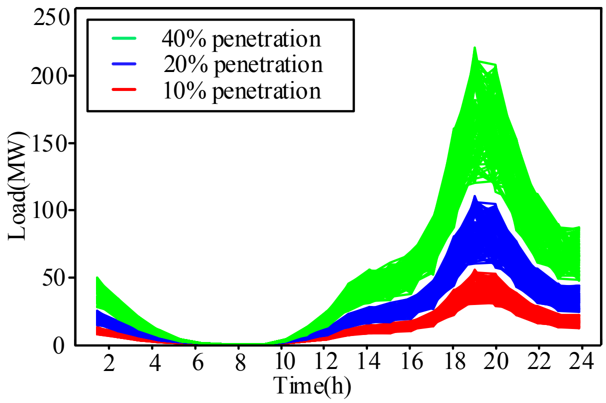


Fig. 4. EVs load due to different penetration levels.

B. *Implications of Risk Aversion Level*

This subsection studies the influence of different risk aversion coefficients on optimal quantity of power obtained from distributed PV's output and different electricity markets. The total installed capacity of distributed PV is 24MW, the confidence level is 95%. The efficient frontier of power supply company's expected profit and CVaR with γ varying from 0 to 1 is represented in Fig. 5. It is can be seen that with a higher risk aversion level, the expected profit is lower, and CVaR is higher, which means that the power supply company's probable expected profit for the lowest 5% increases, and therefore the power supply company has a lower financial risk. When γ is very small, value of CVaR is very low even negative, which means that the power supply company would rather bear greater risk to get higher expected returns, and vice versa.

Fig. 6 shows optimal quantities of power obtained from distributed PV's output and different electricity markets under different risk aversion cases, respectively. It is obvious that with higher values of γ, percentage of power purchase from the day-ahead market, which is supplied to the net load, is lower, percentage of power purchase from forward contracts is higher, and power obtained from distributed PV's output is lower, and vice versa.

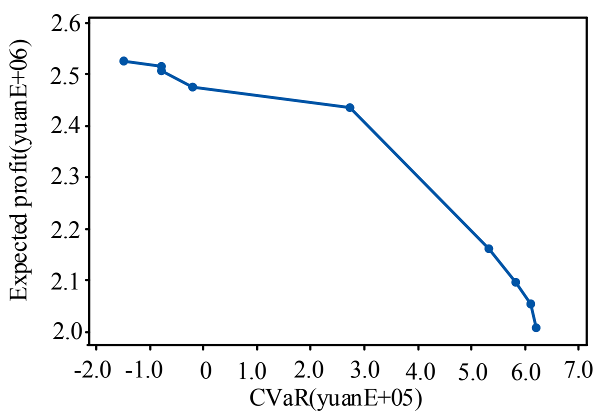


Fig. 5. Efficient frontier of Power Supply Company's expected profit and CVaR

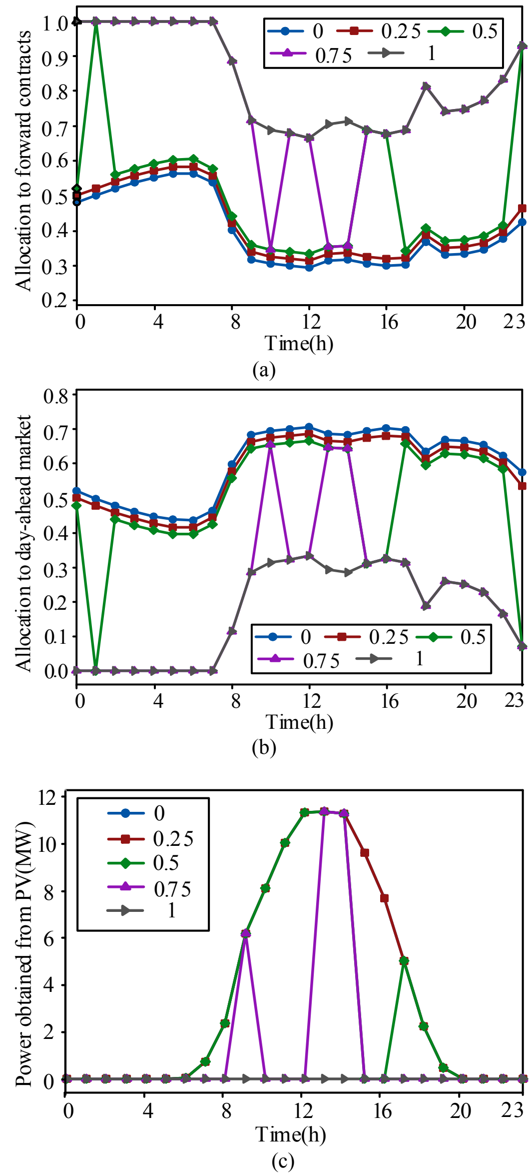


Fig. 6. Optimal portfolio allocation under different risk aversion levels: (a) and (b) shows percentage of power purchase supplied to the net load from different markets, respectively.

Power supply company reduces risk depending on market price fluctuation and load uncertainty caused by distributed PV's output by reducing power obtained from distributed PV's output and increasing power purchase from forward contracts to reduce the overall risk.

C. *Implications of Confidence Level*

In this subsection, the influence of confidence level in the model is investigated. The total installed capacity of distributed PV is 24MW, and the risk aversion coefficient is 0.5. Table III is the results of the expected profit, CVaR and VaR under different confidence levels. Table III shows that CVaR, VaR and expected profit increase when α decreases, and in this process, CVAR is always less than VAR.

Although CVaR and VaR increase when α decreases, the probability of profit lower than the value of VaR increases, which is caused by the lower confidence level. Consequently, it is useless comparing the risk aversion results under different confidence levels. A higher CVaR under a lower confidence level does not mean the risk of profit loss is lower. Therefore, in the proposed model, a reasonable confidence level should be predetermined. From Table III, CVaR does not obviously change with the confidential level varying from 95% to 99%, so 95% as the confidence level is good enough for the model.

D. Impact of EVs Penetration Levels

This subsection studies the influence of the EVs penetration levels in the optimization model. The risk aversion level is fixed with γ=0.5, the confidence level is 95%, and the total installed capacity of distributed PV is 24 MW. Table IV is the results of expected profit, CVaR and VaR under different EVs penetration levels. Table IV shows that with EVs market penetration level increases, the expected profit gradually increases caused by an increase in total load, and CVaR and VaR gradually decreases, which indicates that the risk gradually increased caused by an increase in load uncertainty. Fig. 7 shows optimal quantities of power to be obtained from distributed PV's output and different electricity markets. According to Fig. 4 and Fig.7, it can be seen that, with the increase in EVs market penetration level, percentage of power purchase from forward contracts increases to bear less risks exposure to changing electricity price, at the same time, the power obtained from distributed PV's output decreases to reduce the risks of load uncertainty caused by uncertainty in PV's output, so total risk is reduced.

E. Impact of Distributed PV Capacity

In this study, the risk aversion γ=0.5, the confidence level α=95% and EVs penetration of 0% are assumed.

TABLE III
EXPECTED PROFIT, CVAR AND VAR UNDER DIFFERENT CONFIDENCE LEVELS

α	expected profit(yuan)	CVaR (yuan)	VaR(yuan)
0.99	2414893.42	253127.77	278559.81
0.95	2435659.31	271732.62	318371.25
0.9	2542379.83	291279.15	347808.24
0.8	2748784.37	340696.54	459730.19

TABLE IV
EXPECTED PROFIT, CVAR AND VAR UNDER DIFFERENT EVS PENETRATION LEVELS

penetration levels	expected profit(yuan)	CVaR (yuan)	VaR(yuan)
0%	2435659.31	271732.62	318371.25
10%	2461260.85	266786.73	315630.43
20%	2475662.66	263489.48	313803.25
40%	2492880.70	260332.54	311982.12

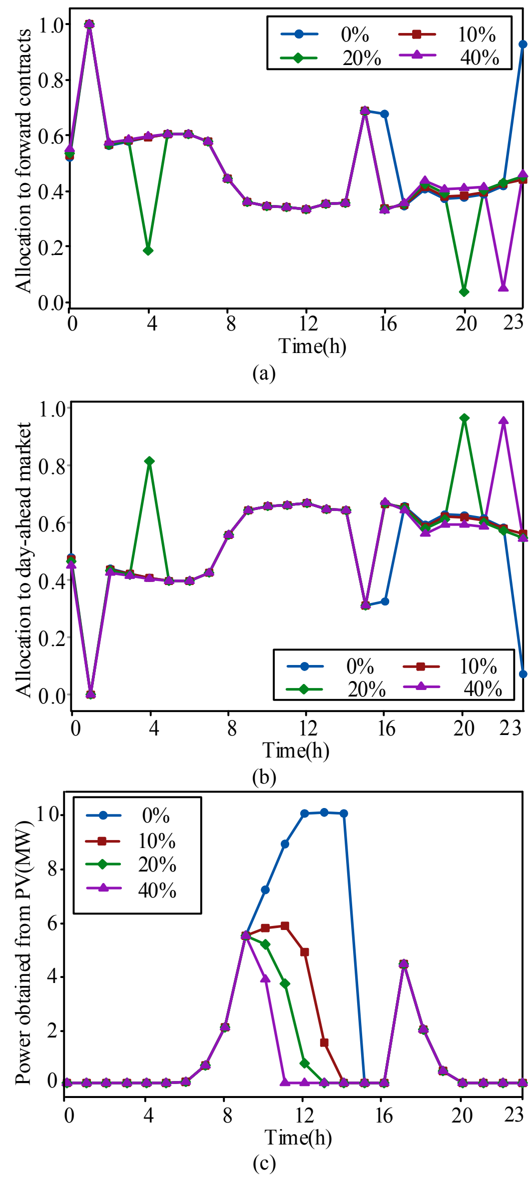


Fig. 7. Optimal portfolio allocation under EVs penetration levels. (a) and (b) shows the percentage of the net load allocated to different contracts, respectively.

Fig. 8 is curves of expected profit, CVaR and VaR under different installed capacities of distributed PV. The primary y axis on the left is for CVaR and VaR value and the other y axis on the right is for expected profit value. Fig.8 shows that CVaR and VaR decrease, and the expected profit increases with the increase in installed capacity of distributed PV. This means that both the expected profit and the financial risk of the profit would be increased by increasing installed capacity of distributed PV. Fig.9 shows power obtained from distributed PV. Referencing to Fig.8 and Fig.9, it can be seen that optimal quantity of power obtained from distributed PV's output does not increase exponentially with the increase of its capacity due to the increase in the risk caused by the distributed PV, but gradually slows, which balances the relationship between profit and risk.

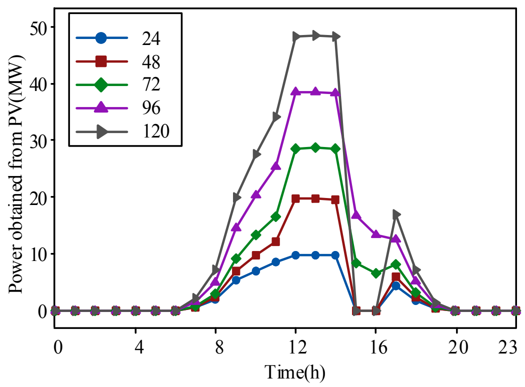


Fig. 8. Power obtained from distributed PV under different installed capacities of distributed PV.

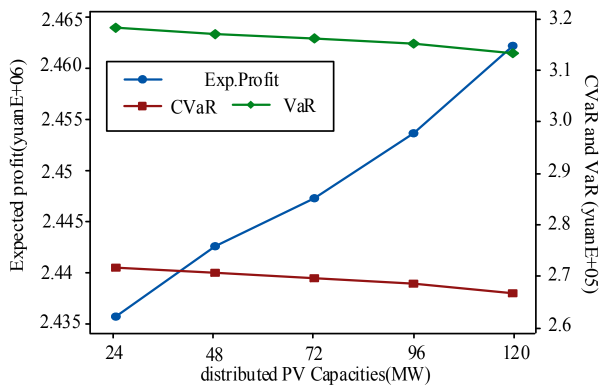


Fig. 9. Power supply company's expected profit, CVaR and VaR under different installed capacities of distributed PV

V. Conclusion

In this paper, a day-ahead portfolio optimization model for power supply company with the consideration of distributed PV and EVs was proposed. The uncertainty of load and price and the expected cost of errors were considered. CVaR was utilized as the risk aversion measure in the proposed model, optimized by linear programming, and solved by Yalmip. Simulation results demonstrated that the proposed model can optimize the electricity purchased from long-term contract, day-ahead market and distributed PVs, therefore minimizing the risk the power supply company faced. Risk aversion level and confidence level in the optimization model were additional factors that can have an impact on the quantity of power to be obtained from distributed PV's output and different electricity markets. The expected profit and financial risk increased as the EVs market penetration levels increased. Also, the expected profit and financial risk increased by increasing the installed distributed capacity of PV.

Acknowledgement

This work was supported by the National Key R&D Program of China (2018YFB0904200), the National Natural Science Foundation of China (51577067), the Beijing Natural Science Foundation of China (3162033), the Hebei Natural Science Foundation of China (E2015502060), the State Key Laboratory of Alternate Electrical Power System with Renewable Energy Sources (LAPS18008), the Headquarters Science and Technology Project of State Grid Corporation of China (SGCC)(NY7116021), the Open Fund of State Key Laboratory of Operation and Control of Renewable Energy & Storage Systems (China Electric Power Research Institute) (5242001600FB), the Fundamental Research Funds for the Central Universities (2018QN077). J.P.S. Catalão acknowledges the support by FEDER funds through COMPETE 2020 and by Portuguese funds through FCT, under Projects SAICT-PAC/0004/2015 - POCI-01-0145-FEDER-016434, POCI-01-0145-FEDER-006961, UID/EEA/50014/2013, UID/CEC/50021/2013, UID/EMS/00151/2013, and 02/SAICT/2017 - POCI-01-0145-FEDER-029803, and also funding from the EU 7th Framework Programme FP7/2007-2013 under GA no. 309048.

References

[1] K. Clement-Nyns, E. Haesen, and J. Driesen, "The impact of charging plug-in hybrid electric vehicles on a residential distribution grid," *IEEE Trans. Power Systems*, vol. 25, pp. 371-380, Feb. 2010.

[2] A. D. Hilshey, P. D. Hines, P. Rezaei, and J. R. Dowds, "Estimating the impact of electric vehicle smart charging on distribution transformer aging," *IEEE Trans. Smart Grid*, vol. 4, pp. 905-913, Jun. 2013.

[3] Q. Chen, F. Wang, B.M. Hodge, J. Zhang, Z. Li, M. Shafie-Khah, J.P.S Catalão, "Dynamic Price Vector Formation Model Based Automatic Demand Response Strategy for PV-assisted EV Charging Station," *IEEE Trans. Smart Grid*, vol. 8, pp.2903-2915, Apr. 2017.

[4] P. P. Barker and R.W. De Mello, "Determining the impact of distributed generation on power systems. I. Radial distribution systems," in *Proc.2000 IEEE Power Engineering Society Summer Meeting*, pp.1645-1656.

[5] S. Eftekharnejad, V Vittal, G. T. Heydt, B. Keel, and J. Loehr, "Impact of increased penetration of photovoltaic generation on power systems,". *IEEE trans. power systems*, vol. 28, pp.893-901.

[6] F. Wang, L. Zhou, H. Ren, X. Liu, S. Talari, M. Shafie-khah, and J. P.S. Catalão, "Multi-Objective Optimization Model of Source-Load-Storage Synergetic Dispatch for a Building Energy Management System Based on TOU Price Demand Response," *IEEE Trans. Industry Applications*, 2018, 54(2):1017-1028. doi: 10.1109/TIA.2017.2781639

[7] F. Wang, H. Xu, T. Xu, K. Li, M. Shafie-khah, and J. P.S. Catalão, "The values of market-based demand response on improving power system reliability under extreme circumstances," *Appl. Energy*, vol. 193, pp. 220–231, May. 2017, DOI: 10.1016/j.apenergy.2017.01.103

[8] F. Wang, K. Li, C. Liu, Z. Mi, M. Shafie-Khah and J.P.S Catalão, "Synchronous Pattern Matching Principle Based Residential Demand Response Baseline Estimation: Mechanism Analysis and Approach Description," *IEEE Trans. Smart Grid*, April 2018, Early Access. doi: 10.1109/TSG.2018.2824842.

[9] F. Wang, K. Li, N. Duic, Z. Mi, B.M. Hodge, M. Shafie-Khah and J.P.S Catalão, "Association Rule Mining Based Quantitative Analysis Approach of Household Characteristics Impacts on Residential Electricity Consumption Patterns," Energy Convers. Manag., 2018, vol. 171, pp. 839-854. doi.org/10.1016/j.enconman.2018.06.017

[10] Y. Sun, F. Wang, B. Wang, Q. Chen, N.A. Engerer and Z. Mi, "Correlation feature selection and mutual information theory based quantitative research on meteorological impact factors of module temperature for solar photovoltaic systems," *Energies*, 2017, 10(1): 7. doi.org/10.3390/en10010007

[11] F. Wang, Z. Zhen, Z. Mi, H. Sun, S. Su, and G. Yang, "Solar irradiance feature extraction and support vector machines based weather status pattern recognition model for short-term photovoltaic power forecasting," *Energy Build.*, vol. 86, pp. 427–438, Feb. 2015, DOI: 10.1016/j.enbuild.2014.10.002

[12] F. Wang, Z. Zhen, C. Liu, Z. Mi, B. Hodge, M. Shafie-khah, and J. P. S. Catalão, "Image phase shift invariance based cloud motion displacement vector calculation method for ultra-short-term solar PV power forecasting," Energy Convers. Manag., vol. 157, pp. 123-135, Jan. 2018, DOI:10.1016/j.enconman.2017.11.080

[13] M. Rana, I. Koprinska, and V. G. Agelidis, "Univariate and multivariate methods for very short-term solar photovoltaic power forecasting," *Energy Convers. Manag.*, vol. 121, pp. 380–390, 2016, DOI: 10.1016/j.enconman.2016.05.025

[14] F. Wang, Z. Mi, S. Su, and H. Zhao, "Short-Term Solar Irradiance Forecasting Model Based on Artificial Neural Network Using Statistical Feature Parameters," *Energies*, vol. 5, pp. 1355–1370, Dec. 2012, DOI: 10.3390/en5051355

[15] F. Wang, Z. Zhen, B. Wang and Z. Mi, "Comparative Study on KNN and SVM Based Weather Classification Models for Day Ahead Short Term Solar PV Power Forecasting," *Appl. Sci.*, 2018, 8(1):28. doi.org/10.3390/app8010028

[16] M. J. Punjabi, P. G. Awate, R. Gajbhiye, S. A. Soman, and K.V. Prasad, "Short term portfolio optimization for load serving entity considering multiple exchanges and ramping constraints," in *Proc.2014 IEEE PES Innovative Smart Grid Technologies Conf.*, pp. 1-5.

[17] F. Gökgöz and M. E. Atmaca, "Financial optimization in the Turkish electricity market: Markowitz's mean-variance approach," *Renewable and Sustainable Energy Reviews*, vol. 16, pp. 357-368, Jan. 2012.

[18] Q. Wang, C. Li, F. Wen, and N. Xu, "Risk assessment and control for distribution companies in electricity market environment," in *Proc. 2008 Electric Utility Deregulation and Restructuring and Power Technologies Conf.*, pp. 335-339.

[19] A. A. Thatte, L. Xie., D. E. Viassolo, and S. Singh, "Risk Measure Based Robust Bidding Strategy for Arbitrage Using a Wind Farm and Energy Storage," *IEEE Trans. Smart Grid*, vol. 4, pp. 2191-2199, Dec. 2013.

[20] R. Wang, Y. Li, and H. Wang, "CVaR based purchasing portfolio for load serving entities with distributed energy," in *Proc. 2009 IEEE International Conference on Sustainable Power Generation and Supply*, pp. 1-6.

[21] Á. Orca and J. Prina, "Power portfolio optimization considering locational electricity prices and risk management," *Electric Power Systems Research*, vol. 109, pp. 80-89 Apr. 2014

[22] Z. F. Tan, G. Wang, L. W. Ju, Q. K. Tan, and W. H. Yang, "Application of CVaR risk aversion approach in the dynamical scheduling optimization model for virtual power plant connected with wind-photovoltaic-energy storage system with uncertainties and demand response," *Energy*, vol.124, pp.198-213, Apr.2017.

[23] R. T. Rockafellar and S. Uryasev, "Optimization of conditional value-at-risk," *Journal of Risk*, vol. 2, pp. 21-41, 2000.

[24] S. H. Karaki, R. B. Chedid, and R. Ramadan, "Probabilistic performance assessment of autonomous solar-wind energy conversion systems," [J]. *IEEE Trans. Energy Conversion*, vol. 14, pp. 766-772 Sep. 1999.

[25] K. Qian, C. Zhou, M. Allan, and Y. Yuan, "Modeling of load demand due to EV battery charging in distribution systems," *IEEE Trans. Power Systems*, vol. 26, pp. 802–810, May 2011.