Multi-Objective Stochastic Scheduling Optimization Model for Connecting a Virtual Power Plant to Wind-Photovoltaic-Electric Vehicles Considering Uncertainties and Demand Response

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Abstract: A stochastic chance-constrained planning method is applied to build a multi-objective optimization model for virtual power plant scheduling. Firstly, the implementation cost of demand response is calculated using the system income difference. Secondly, a wind power plant, photovoltaic power, an electric vehicle group and a conventional power plant are aggregated into a virtual power plant. A stochastic scheduling model is proposed for the virtual power plant, considering uncertainties under three objective functions. Thirdly, a three-stage hybrid intelligent solution algorithm is proposed, featuring the particle swarm optimization algorithm, the entropy weight method and the fuzzy satisfaction theory. Finally, the *Yunnan* distributed power demonstration project in China is utilized for example analysis. Simulation results demonstrate that when considering uncertainties, the system will reduce the grid connection of the wind power plant and photovoltaic power to decrease the power shortage punishment cost. The average reduction of the system power shortage punishment cost and the operation revenue of virtual power plant are 61.5% and 1.76%, respectively, while the average increase of the system abandoned energy cost is 40.4%. The output of the virtual power plant exhibits a reverse distribution with the confidence degree of the uncertainty variable. The proposed algorithm rapidly calculates a global optimal set. The electric vehicle group could provide spinning reserve to ensure stability of the output of the virtual power plant. Demand response could optimize customers' power consumption behaviors and improve the grid connection space of the virtual power plant. The electric vehicle group and demand response could achieve a linkage optimization effect between the generation side and demand side, achieving optimal system scheduling objectives.

Keywords: virtual power plant; demand response; electric vehicle group; multi-objective; uncertainties

Nomenclature

abbreviations		v_{out}	cut-out wind velocity
VPP	virtual power plant	v_{rated}	rated wind velocity
DR	demand response	ψ, ζ	shape parameters of the <i>Beta</i> distribution
PBDR	price-based DR	$g_{PV}^{\max}$	maximum PV output power
IBDR	incentive-based DR	μ_{PV}	average value of the PV output
WPP	wind power plant	σ_{PV}	standard value of the PV output
PV	photovoltaic generators	$f(g_{PV,t})$	the PDF of the solar radiation intensity
CPP	conventional power plant	$N_{EV,t}^{dis}$	discharging electric vehicle number at time t
EVG	plug-in electric vehicle group	$N_{EV,t}^{chr}$	charging electric vehicle number at time t
GC	generating companies	α_i	confidence level of the i -th objective function
ISO	independent system operator	ξ	stochastic vector
DERs	distributed energy resource	x	n -dimensional decision vector
PDF	probability density function	$\Pr\{\cdot\}$	probability of event occurring in $\{\cdot\}$
Set		β_j	confidence level of constraint $g_j(x, \xi) \leq 0$
s, t	index for time	α_1	confidence level of f_1
W	index for WPP	ρ_s	unit power shortage compensation price
PV	index for PV	α_2	confidence level of f_2
EV	index for EV	ρ_w	grid connection power prices of the WPP
CPP	index for CPP	ρ_{PV}	grid connection power prices of the PV
i, m	index for objective functions	g_w^*	actual available outputs of the WPP
j	index for stochastic constraints	g_{PV}^*	actual available outputs of PV
Variable		α_3	confidence level of f_3
ΔL_s	load demand changes after PBDR at time s	$a_{CPP}, b_{CPP}, c_{CPP}$	cost coefficients of CPP power generation
L_t	load demand after PBDR at time t	N_{CPP}^{cold}	cold-startup cost of the <i>CPP</i>
C_t^P	system power sale income change before and after the PBDR	N_{CPP}^{hot}	hot-startup of the <i>CPP</i>
C_t^I	system incremental cost of implementing IBDR	$T_{CPP}^{\min}$	minimum allowed downtime of the CPP
ΔL_t^I	load change amount at time t	$T_{CPP,t}^{off}$	continuous downtime of the CPP at time t
$\Delta L_t^{I,u}$	upstream reserve load at time t	T_{CPP}^{cold}	cold-startup time of the CPP
$\Delta L_t^{I,d}$	downstream reserve load at time t	ϕ_w	power consumption rate of the WPP
$s_t^{I,d}, s_t^{I,u}$	0-1 variable, 1 means reserve load is provided,	ϕ_{PV}	power consumption rate of the PV
v	wind velocity	ϕ_{CPP}	power consumption rate of the CPP
$g_{w,t}$	WPP output at time t	$g_{GC,t}$	electricity purchasing from GC at time t
$g_{PV,t}$	PV output at time t	β_1	confidence level of demand and supply balance constraint
$g_{EV,t}$	EVG output at time t	$g_{CPP}^{\max}$	upper limitation of the CPP output
$g_{EV,t}^{dis}$	discharging power of the EVG at time t	$g_{CPP}^{\min}$	lower limitation of the CPP output
$g_{EV,t}^{chr}$	charging power of the EVG at time t	Δg_{CPP}^+	upper climbing limitation of the CPP output

$\bar{f}_i$	minimum value of $f_i(x, \xi)$	Δg_{CPP}^-	lower climbing limitation of the CPP output
f_1	objective function of the minimum system compensation cost	M_{CPP}^{on}	shortest startup time of the CPP
$\Delta L_{S,t}$	power shortage load at time t	$T_{CPP,t-1}^{on}$	continuous operation time of the CPP at time $t-1$
f_2	objective function of the minimum VPP abandoned power	M_{CPP}^{off}	shortest downtime of the CPP
f_3	objective function of the maximum VPP operation income	$T_{CPP,t-1}^{off}$	continuous downtime of the CPP at time $t-1$
$\pi_{W,t}$	generation incomes of the WPP at time t	$u_{CPP,t}$	status variable of the CPP at time t ; 1 means the CPP is in operation, and 0 means the CPP is not in operation
$\pi_{PV,t}$	generation incomes of the PV at time t	Q_t	storage energy of the EVG at time t
$\pi_{EV,t}$	generation incomes of the EV at time t	ρ_{EV}	loss rate of charging-discharging power
$\pi_{CPP,t}$	generation incomes of the CPP at time t	$\bar{g}_{EV,t}^{chr}$	maximum charging power of the EVG at time t
$D_{CPP,t}$	startup-shutdown cost of the CPP at time t	$\bar{g}_{EV,t}^{dis}$	maximum discharging power of the EVG at time t
$g_{CPP,t}$	power output of the CPP at time t	β_2	confidence levels of the EVG charging power constraint
$G_t^{VPP,max}$	maximum output power of the VPP	β_3	confidence levels of the EVG discharging power constraint
R_t^{VPP}	installed capacity for reserve demand of the VPP at time t	ΔL_t^{max}	maximum curtailment load at time t
d_i	information deviation of $\bar{f}_i$	β_4, β_5	confidence levels of the □load curtailment constraint
λ_i	weight coefficient of $\bar{f}_i$	L_D^P	lower climbing limitation of the load produced by PBDR
Parameter		L_U^P	upper climbing limitation of the load produced by PBDR
e_{st}	demand-price elasticity	L_D^I	lower climbing limitation of the load produced by IBDR
P_t^0	electricity price before PBDR	Q_0	storage energy of the EVG at the initial time
L_s^0	load demand before PBDR	$X_{t-1}^{P,on}$	continuous operation time of PBDR
ΔP_t	electricity price changes after PBDR at time t	$X_t^{P,off}$	continuous downtime of PBDR
δ	high price compensation rate	L_U^I	upper climbing limitation of the load produced by IBDR
τ	discount price rate	$T^{P,on}$	minimum load operation time of PBDR
φ	shape factor	$T^{P,off}$	minimum load downtime time of PBDR
$\mathcal{G}$	scale factor	$X_{t-1}^{I,on}$	continuous operation time of IBDR
$v_{w,t}$	real-time wind velocity at time t	$X_t^{I,off}$	continuous downtime of IBDR
g_R	WPP rated output	$T^{I,on}$	minimum load operation time of IBDR
v_{in}	cut-in wind velocity	$T^{I,off}$	minimum load downtime time of IBDR
β_6	confidence levels for upstream reserve constraint	$S^{I,max}$	upper limitation of the IBDR demand response time
β_7	confidence levels for downstream reserve constraint	ΔL_t^I	virtual output produced by IBDR at time t
r_1	reserve coefficient of the load	ΔL_t^P	virtual output produced by PBDR at time t
r_2	reserve coefficient of the WPP	$\Delta \bar{L}_t^P$	maximum output of PBDR at time t
r_3	reserve coefficient of the PV	$\Delta \bar{L}_t^I$	maximum output of IBDR at time t
r_4	reserve coefficient of the EV	S_t^P	status variable of PBDR; 1 means PBDR is scheduled, and 0 means PBDR is not scheduled.
ΔL_t^{max}	maximum curtailment load at time t	S_t^I	status variable of IBDR; 1 means PBDR is scheduled, and 0 means PBDR is not scheduled.

1 Introduction

Due to traditional energy shortage and environmental pollution problems, renewable energy power generation has attracted increased attention. Distributed energy resources (DERs), especially wind power and solar photovoltaic power, are playing increasingly important roles in energy structures [1]. However, limited by the characteristics of small capacity, large quantity and geographical dispersion, the grid connection cost of DERs is relatively high. DER grid connection could also affect the stability of system operation [2]. Thus, the virtual power plant (VPP) is proposed as a new technology for DERs in the power market [3]. A VPP can effectively integrate, aggregate and manage DERs, including distributed generators (DGs), energy storage systems and controllable loads [4]. In particular, the rapid development of smart grid technology promotes reasonable resource configuration and provides solid support for VPP operation.

In recent years, many countries have performed VPP pilot projects. In 2007, the University of Kassel formed the largest VPP pilot project by integrating a wind turbine, a solar energy system, a biogas power plant and a hydro power plant [5]. In 2009, a smart grid project connecting electric vehicles (EVs) in Denmark took the uncertainty of large-scale wind power output into consideration and introduced VPP technology to manage the EVs' charging-discharging power [6]. In 2012, the Rhineland Group in Germany began operating the first commercial VPP [7]. In 2008, a distributed energy station in Guangdong University City, China began operation to meet the load demand of the University City [8]. In 2011, the Zhangbei wind-photovoltaic-storage-transmission project began operation in China, integrating a wind power plant (WPP), photovoltaic power (PV), an energy storage system and power transmission [9]. In 2014 in Xiaozhongdian, China, a wind-photovoltaic-hydro distributed power demonstration project successfully connected the China Southern Power Grid and began commercial operation [10].

Research regarding VPP generally begins from a VPP itself and focuses on how to optimize VPP operation based on capacity configuration and operation coordination. Spyros et al. [11] defined the concept and control mode of a VPP. Moghaddam et al. [12] summarized the essential status quo and development prospect of domestic and foreign VPPs. Omid et al. [13] described the principles of a VPP considering the operational concepts and requirements from participation in active network management. Compared with micro-grids, VPPs particularly emphasize top-down control to achieve controllable output through multi-resource, multi-time and multi-space coordinate scheduling [14]. Then, mathematical models

are constructed for VPP scheduling. Tascikaraoglu et al. [15] evaluated the virtual power plant strategy, including a hybrid system consisting of wind, solar, hydrogen and thermal power systems. Shayeghi et al. [16] presented the optimal integrated participation model of wind and PV energy, including storage devices and dispatchable distributed generations to increase their revenues. Riveros et al. [17] presented a methodology to evaluate the optimal bidding strategy of a VPP composed of a combined heat and power system coupled with district heating and renewable-energy sources. The above works from the literature study the basic concept, operation optimization and scheduling model of a VPP but fail to analyze the uncertainty influence of the WPP, PV and other factors on the system's stable operation.

Some studies have focused on how to overcome the fluctuation problem of VPP output. Perfumo et al. [18] developed a mathematical model aimed at the design of a model-based feedback control strategy. Zhang et al. [19] studied the optimal scheduling model of a VPP considering smart homes' energy consumption. Controllable units, energy storage systems and controllable loads often provide backup service for VPP power generation [20]. Shafie-khah et al. [21] proposed a market-based VPP model to allow individual DER units to access the current electricity markets. A VPP can optimally operate the generation units, including a wind turbine, a solar unit, a fuel cell and a storage battery [22]. Then, to describe the output uncertainty of the WPP and PV, Peik-Herfeh et al. [23] used a two-point assessment method to obtain two values on each side of the predicted value to present the output fluctuation of the unit. Yang et al. [24] assumed that wind velocity obeys the Weibull distribution and used the maximum likelihood estimation to obtain the distribution parameters and calculate the wind turbine's output. Yang et al. [25] introduced a robust optimization method to optimize the scheduling scheme by adjusting the robust coefficient to obtain a scheme set. Braslavsky et al. [26] presented an optimal scheduling model and construct a simulation method with five classical scenarios for uncertainty factors. Morteza et al. [27] presented a robust optimization-based decision-making tool for self-scheduling of a VPP in the uncertain environment of electricity markets. The proposed methods and models may be effective for overcoming the uncertainty influence, but they can only handle the constraint conditions and do not address objective functions with stochastic variables. Then, with the rapid development of the smart grid, customers can actively respond to system scheduling. The research regarding how to cooperate with VPP operation by utilizing customers should be further developed.

Two-way interactive technology could provide a technological foundation for demand-side

participation in optimal scheduling of the generation side. Customer guidance measures could optimize customer behavior to respond to system power generation scheduling. Demand response (DR) refers to the market-oriented consumption behavior in electricity grids. DR can be classified into price-based demand responses (PBDRs) and incentive-based demand responses (IBDRs) [28]. Dimopoulos et al. [29] analyzed the economic benefits of small-scale generation and electric vehicles under different demand response strategies. Bracco et al. [30] designed a dynamic optimization-based architecture for polygeneration microgrids with tri-generation, storage system demand response and electrical vehicles. DR could result in load peak-valley shifting and reduce the uncertainty caused by renewable energy grid connections [31]. In addition, DR plays an increasingly important role in balancing short-term supply and load demand and dealing with fluctuations in renewable energy supplies. However, the application of the DR model has not been sufficiently discussed in previous studies of VPP management.

Previous studies have already studied the optimization of VPP operation and achieved favorable results. However, various insufficiencies still exist. Firstly, some studies took the uncertainty of the WPP and PV into consideration and analyzed the uncertainty influence on VPP operation. The robust optimization method is the main tool to analyze the uncertainties of the WPP and PV. However, the method could only handle the constraint conditions without discussing the objective functions with stochastic variables. The paper uses a stochastic chance-constrained planning method to overcome the uncertainty factors, which could handle the stochastic variables in the constraint conditions and objective functions. Secondly, DR could optimize customers' power consumption behavior. Customers will increase power consumption in valley periods and decrease power consumption in peak periods. In particular, when power supply cannot meet power demand, customers can reduce power consumption. The curtailed load can be regarded as virtual power output. The virtual power output can provide reserve capacity for the WPP and PV, which could ensure stable VPP output and optimize VPP scheduling results. However, the previous studies rarely discuss the influence of demand response on VPPs, especially PBDR. The paper integrates IBDR into VPP components and discusses the influence of PBDR on VPP operation. Thirdly, because VPP operation has plural requirements, the VPP scheduling model has multiple objectives. A reasonable mathematical model and solution algorithm are important for optimal operation of a VPP. The contributions of this study are as follows:

- A multi-objective optimization model for VPP stochastic scheduling considering uncertainties

and DR is proposed. The model considers the uncertain factors of the DR, WPP, PV and EVG. The minimum system compensation cost, the minimum abandoned power cost and the maximum VPP operation income are taken as the optimization objective functions.

- A stochastic chance-constrained method is introduced to overcome the uncertainties of the DR, WPP, PV and EVG. The study focuses on analyzing the risk level and choosing the optimal confidence degree of VPP scheduling. Spinning reserve constraints are satisfied with certain confidence degrees to discuss the risk level of VPP scheduling under different confidence degrees and risk coefficients.

- The particle swarm optimization algorithm, entropy weight method and fuzzy satisfaction theory are applied to construct a three-stage hybrid intelligent solution algorithm. Cloud evolutionary thought and stochastic technology are used to evolve an excellent particle swarm. The entropy method can solve the single objective weight to form a comprehensive optimization model. The fuzzy satisfaction theory can select the optimal decision.

The remainder of this paper is organized as follows. Section 2 presents the demand response model, including a PBDR model and IBDR model. Section 3 constructs a multi-objective optimization model for VPP stochastic scheduling, including model assumptions, uncertainty analyses and model formulation. Section 4 proposes a three-stage hybrid intelligent solution algorithm based on the particle swarm optimization algorithm, the entropy method and the fuzzy satisfaction theory. China's Yunnan distributed energy demonstration project is taken as a case study in Section 5. Section 6 presents the study's primary conclusions.

2 Demand Response Model

Demand response mainly includes price-based demand response (PBDR) and incentive-based demand response (IBDR). DR can optimize customers' power consumption behavior to participate in the dynamic scheduling of VPP operation.

2.1 Price-based DR model

PBDR can optimize customers' power consumption behavior and transfer power consumption period by implementing a time-of-use (TOU) price. The influence of PBDR on customers' behavior can be described by power demand-price elasticity in Eq. (1) [10].

$$e_{st} = \frac{\Delta L_s / L_s^0}{\Delta P_t / P_t^0} \begin{cases} e_{st} < 0, \text{ if } s = t \\ e_{st} \geq 0, \text{ if } s \neq t \end{cases} \quad (1)$$

Eq. (1) describes the relationship between load demand and electricity price. When P_t^0 , ΔP_t , L_s^0 and e_{st} are known, ΔL_s can be obtained.

If the electricity price changes in diverse periods, customers can respond in two ways. In the first way, they can only be on or off in the case that some loads are not able to move from one period to another (e.g., illuminating loads). Such loads have sensitivity in a single period called “self-elasticity,” which always has a negative value [32]. In the second way, some consumption can be transferred from the peak period to off-peak or low periods (e.g., process loads). Such behavior is called multi-period sensitivity and is evaluated by “cross-elasticity,” which is always positive [33]. The detailed mathematical description is as follows:

1) If $s=t$, e_{st} is called self-elasticity. Only demand curtailment can occur in this method. Therefore, e_{st} is always negative, and the load change is always negative.

2) If $s \neq t$, e_{st} is called cross-elasticity. Demand shifting can occur in this method. e_{st} is always positive, and the load change is always positive.

According to the above analysis, both demand curtailment and demand shift can occur in the PBDR. The load change after the PBDR previously calculated in literature [34] does not discuss the detailed calculation method. The load change L_t after PBDR is given by Eq. (2).

$$L_t = L_t^0 \times \left\{ 1 + e_{tt} \times \frac{[P_t - P_t^0]}{P_t^0} + \sum_{\substack{s=1 \\ s \neq t}}^{24} e_{st} \times \frac{[P_s - P_s^0]}{P_s^0} \right\} \quad (2)$$

Combining Eq. (1) and Eq. (2), the system power sale income change before and after PBDR can be calculated by Eq. (3):

$$C_t^P = P_t^0 L_t^0 - (P_t^0 + \Delta P_t) L_t \quad (3)$$

wherein the first term and the second term are the system power sale income before and after PBDR, respectively.

2.2 Incentive-based DR model

IBDR utilizes incentive policies to encourage customers to participate in market adjustment, which could maintain system supply and demand balance [35]. Customers can participate in system

upstream/downstream reserve [34]. The load curtailment and incremental cost of implementing IBDR can be calculated by Eq. (4) and Eq. (5).

$$C_t^I = s_t^{I,d} \delta P_t \Delta L_t^{I,d} + s_t^{I,u} (1 - \tau) P_t \Delta L_t^{I,u} \quad (4)$$

$$\Delta L_t^I = s_t^{I,d} \Delta L_t^{I,d} + s_t^{I,u} \Delta L_t^{I,u} \quad (5)$$

Eq.(4) calculates the system incremental cost of implementing IBDR, including upstream reserve cost and downstream reserve cost. Eq. (5) ensures that $s_t^{I,d}$ and $s_t^{I,u}$ cannot be 1 simultaneously.

3 VPP Stochastic Scheduling Optimization Model

This section constructs a stochastic optimization model of VPP scheduling. Firstly, the basic structure of a VPP is proposed. Secondly, the uncertainty factors of VPP operation are analyzed, which includes VPP uncertainty and DR uncertainty. Thirdly, the dynamic scheduling model for VPP operation is proposed based on the stochastic chance constraint planning theory.

3.1 Proposed model

In this study, the VPP consists of a WPP, PV, EVG and CPP. A day-ahead market structure is used in Fig. 1 [36]. An independent system operator (ISO) receives bids from generating companies (GC) and the VPP to provide energy. Then, according to customers' power demand, the ISO sends signals to customers corresponding to the power price adjustment range and reserve price. Customers change their load demand after receiving price signals. Finally, the ISO simultaneously schedules energy and reserves in the power system considering system constraints and different objective functions.

Fig. 1 Market structure with a VPP

The WPP and PV are the primary power resources to meet the load demand; the EVG and CPP could provide reserve services for power resources with uncertainty output. The EVG must be registered in the VPP central controller before the scheduling period [10]. The VPP central controller can issue orders to the EVG according to the real-time power output state of the WPP and PV by controlling its charging-discharging behavior. Similar to an energy storage system, the EVG could provide a reserve service via the charging-discharging power. Furthermore, the EVG could also connect the demand side and generation side to achieve a linked optimization effect. Therefore, this study introduces an EVG instead of an energy storage system.

PBDR and IBDR are both discussed in this study. PBDR optimizes customers' behaviors to optimize VPP operation. IBDR guides customers to provide reserve services by providing upstream/downstream spinning reserve price signals. Because VPP scheduling depends on perfect communication infrastructure, this study assumes that a smart grid and its communication infrastructure have already been in operation [37].

3.2 Uncertainty analysis

Multiple uncertainties exist in VPP scheduling models. DR customers are quite subjective and change their load demands with respect to electricity prices. The WPP and PV are uncontrollable power resources with uncertain power output.

3.2.1 VPP uncertainty

The uncertainty factors of VPP operation are primarily derived from the uncertain output of the WPP, PV and EVG. The EVG's uncertainty is primarily influenced by customer subjectivity.

(1) WPP output uncertainty

WPP output uncertainty depends on the stochastic characteristic of wind velocity. Though wind velocity appears stochastic in both the short term and long term, large statistical datasets have shown that wind velocity can be approximately described by the Weibull distribution [34] based on the probability density function (PDF) in Eq. (6):

$$f(v) = \frac{\varphi}{g} \left(\frac{v}{g} \right)^{\varphi-1} e^{-(v/g)^\varphi} \quad (6)$$

Eq. (6) can be used to gain the average value and variance of the wind velocity for the corresponding period. After obtaining φ and g , the wind velocity can be simulated using MATLAB tools. The

relationship between WPP output and real-time wind velocity can be described by Eq. (7).

$$g_{w,t}(v_{w,t}) = \begin{cases} 0, & 0 \leq v_t < v_{in}, \quad v_t > v_{out} \\ \frac{v_t^3 - v_{in}^3}{v_{rated}^3 - v_{in}^3} g_R, & v_{in} \leq v_t \leq v_{rated} \\ R, & v_{rated} \leq v_t \leq v_{out} \end{cases} \quad (7)$$

(2) PV output uncertainty

PV output is closely related with solar radiation intensity. The solar radiation intensity is a stochastic variable that obeys the *Beta* distribution [34]; therefore, PV output should also obey the *Beta* distribution. The PDF is given by Eq. (8).

$$f(g_{PV,t}) = \frac{\varphi}{\beta(\psi, \zeta)} \left(\frac{g_{PV,t}}{g_{PV}^{\max}} \right)^{\psi-1} \left(1 - \frac{g_{PV,t}}{g_{PV}^{\max}} \right)^{\zeta-1} \quad (8)$$

$$\beta(\psi, \zeta) = \frac{\Gamma(\psi)\Gamma(\zeta)}{\Gamma(\psi) + \Gamma(\zeta)} \quad (9)$$

wherein $\beta(\psi, \zeta)$ is the *Beta* distribution function. ψ and ζ can be calculated by Eq. (10) and Eq. (11).

$$\psi = \mu_{PV} \left(\frac{\mu_{PV}(1 - \mu_{PV})}{\sigma_{PV}^2} - 1 \right) \quad (10)$$

$$\zeta = (1 - \mu_{PV}) \mu_{PV} \left(\frac{\mu_{PV}(1 - \mu_{PV})}{\sigma_{PV}^2} - 1 \right) \quad (11)$$

After obtaining the PDF of the local solar radiation intensity $f(g_{PV,t})$, the PV output can be simulated.

(3) EVG output uncertainty

The EVG consists of many electric vehicles with different charging-discharging power behaviors. However, in terms of the overall output, the EVG output should obey a certain PDF. The paper takes the mean output value as the actual output of electric vehicles. Therefore, the predicted output of the EVG is primarily influenced by an EV's charging-discharging number. The EVG output can be calculated by Eq. (12):

$$\bar{g}_{EV,t} = N_{EV,t}^{dis} g_{EV,t}^{dis} - N_{EV,t}^{chr} g_{EV,t}^{chr} \quad (12)$$

wherein $\bar{g}_{EV,t}$ is the predicted value of the EVG output. To imitate the EVG's charging-discharging behavior, the EVG output can be divided into the predicted output and the deviation output:

$$g_{EV,t} = \bar{g}_{EV,t} + \hat{g}_{EV,t} \quad (13)$$

According to the EVG's charging-discharging history data, the deviation distribution of the EVG

output can be obtained. The paper assumes $\hat{g}_{EV,t} \sim N(0, \sigma_{EV,t}^2)$ [38]. Then, the EVG output follows

$$g_{EV,t} \sim N(\bar{g}_{EV,t}, \sigma_{EV,t}^2).$$

3.2.2 DR uncertainty

Because customers are subjective, they change their load demands with respect to electricity prices, but the relationship between the load demand and electricity price is uncertain. Traditional customers' psychology model [35] regards curtailed load as a determined value and considers that customers respond to system scheduling according to the expected objective. However, the implementation of PBDR depends on customer willingness. Therefore, the load change produced by PBDR is influenced by other non-economic factors, which will result in strong uncertainty. IBDR primarily constrains customer behavior via a signed contract, which effectively reduces the customer default rate. However, due to the uncertainty of the external environment, the incomplete information, the subjective characteristics of decision-makers and other factors, IBDR also has uncertainty. The uncertainty of PBDR and IBDR can cause power fluctuations, and therefore ΔL_t^P and ΔL_t^I are stochastic variables.

3.3 Model formulation

3.3.1 Stochastic chance constraint planning

To consider the influence of stochastic variables on system scheduling, this section introduces the stochastic constraint planning method [39]. The stochastic chance constraint method is mainly used to solve decision problems with stochastic variables, wherein the decision must be made before obtaining the real values of stochastic variables. Considering the influence of stochastic variables, the decisions are allowed to deviate from the constraints to a certain degree to get closer to the actual situation. The confidence level should be set considering the decision-maker's tolerance to ensure a rational decision. The probability of the decision meeting the constraints should not be lower than the given confidence level. The multiple-objective chance constraint-planning models can be described as:

$$\begin{cases} \min [\bar{f}_1, \bar{f}_2, \dots, \bar{f}_m] \\ s.t. \quad \Pr(f_i(x, \xi) \leq \bar{f}_i, i = 1, 2, \dots, m) \geq \alpha_i \\ \quad \Pr(g_j(x, \xi) \leq 0, j = 1, 2, \dots, m) \geq \beta_j \end{cases} \quad (14)$$

3.3.2 VPP stochastic scheduling model

DR can smooth the load demand curve and provide more grid connection space for the VPP, but DR

also influences system income. The system power sale income difference before and after PBDR could be regarded as a DR implementation cost. This paper takes the power shortage cost and DR implementation cost as the system compensation cost and takes the minimum system compensation cost as the objective function.

$$\begin{cases} \min \bar{f}_1 \\ s.t. \Pr\{f_1 \leq \bar{f}_1\} \geq \alpha_1 \\ f_1 = \sum_{t=1}^T [(C_t^P + C_t^I) + \rho_S \Delta L_{S,t}] \end{cases} \quad (15)$$

wherein the confidence level α_1 is used to constrain the probability of the objective function value being lower than the minimum value. When α_1 equals 1, the system should realize the optimization scheduling of VPP operation. The decision-makers will hope the optimization degree of the objective function is better when α_1 is higher. Then, to maximize the energy-saving benefit of VPP operation, the minimum abandoned energy cost of the VPP should be taken as another objective function:

$$\begin{cases} \min \bar{f}_2 \\ s.t. \Pr\{f_2 \leq \bar{f}_2\} \geq \alpha_2 \\ f_2 = \sum_{t=1}^T [\rho_W (g_{W,t} - g_W^*) + \rho_{PV} (g_{PV,t} - g_{PV}^*)] \end{cases} \quad (16)$$

Eq. (16) take the minimum abandoned energy as the objective function. The abandoned energy mainly includes abandoned wind power and abandoned photovoltaic power.

$$\begin{cases} \max \bar{f}_3 \\ s.t. \Pr\{f_3 \geq \bar{f}_3\} \geq \alpha_3 \\ f_3 = \sum_{t=1}^T \{\pi_{W,t} + \pi_{PV,t} + \pi_{EV,t} + \pi_{CPP,t}\} \\ \pi_{W,t} = \rho_{W,t} g_{W,t} \\ \pi_{PV,t} = \rho_{PV,t} g_{PV,t} \\ \pi_{EV,t} = N_t^{dis} \rho_{EV,t}^{dis} g_{EV,t}^{dis} - N_t^{chr} \rho_{EV,t}^{chr} g_{EV,t}^{chr} \\ \pi_{CPP,t} = \left\{ \rho_{CPP,t} g_{CPP,t} - [a_{CPP} + b_{CPP} g_{CPP,t} + c_{CPP} (g_{CPP,t})^2] - [u_{CPP,t} (1 - u_{CPP,t-1})] D_{CPP,t} \right\} \\ D_{CPP,t} = \begin{cases} N_{CPP}^{hot}, & T_{CPP}^{\min} < T_{CPP,t}^{off} \leq T_{CPP}^{\min} + T_{CPP}^{cold} \\ N_{CPP}^{cold}, & T_{CPP,t}^{off} > T_{CPP}^{\min} + T_{CPP}^{cold} \end{cases} \end{cases} \quad (17)$$

Eq. (17) takes the maximum VPP operation income as the objective function, including the generation

incomes of the WPP, PV, EVG and CPP. The constraints of the proposed model include the demand and supply balance constraint, CPP operation constraint, EVG charging-discharging constraints, DR operation constraint and system reserve constraint.

(1) Demand and supply balance constraint

$$G_t^{VPP} + g_{GC,t} = L_t - s_t^{L,d} \Delta L_t^{L,d} + s_t^{L,u} \Delta L_t^{L,u} \quad (18)$$

$$G_t^{VPP} = g_{W,t} (1 - \varphi_W) + g_{PV,t} (1 - \varphi_{PV}) + (N_{EV,t}^{dis} g_{EV,t}^{dis} - N_{EV,t}^{chr} g_{EV,t}^{chr}) + g_{CPP,t} (1 - \varphi_{CPP}) \quad (19)$$

Because the outputs of the WPP, PV and EVG are stochastic variables, constraint (18) should be rewritten as follows:

$$\Pr \{ G_t^{VPP} + g_{GC,t} = L_t - s_t^d \Delta L_t^d + s_t^u \Delta L_t^u \} \geq \beta_1 \quad (20)$$

(2) CPP operation constraint

$$u_{CPP,t} g_{CPP}^{\min} \leq g_{CPP,t} \leq u_{CPP,t} g_{CPP}^{\max} \quad (21)$$

$$u_{CPP,t} \Delta g_{CPP}^- \leq g_{CPP,t} - g_{CPP,t-1} \leq u_{CPP,t} \Delta g_{CPP}^+ \quad (22)$$

$$(T_{CPP,t-1}^{\text{on}} - M_{CPP}^{\text{on}})(u_{CPP,t-1} - u_{CPP,t}) \geq 0 \quad (23)$$

$$(T_{CPP,t-1}^{\text{off}} - M_{CPP}^{\text{off}})(u_{CPP,t} - u_{CPP,t-1}) \geq 0 \quad (24)$$

wherein $u_{CPP,t}$ is a 0-1 variable; 1 indicates that the CPP is scheduled, and 0 indicates that the CPP is not scheduled.

(3) EVG charging-discharging constraint

During the entire scheduling period T , the relationship between the charging power and discharging power of the EVG should meet the following constraint:

$$\sum_{t=1}^T (Q_0 + g_{EV,t}^{chr} - Q_t)(1 - \rho_{EV}) = \sum_{t=1}^T g_{EV,t}^{dis} \quad (25)$$

Assuming that the EVG cannot charge and discharge at the same time, its charging-discharging behavior should meet the following constraint.

$$g_{EV,t}^{chr} \cdot g_{EV,t}^{dis} = 0 \quad (26)$$

In addition, the charging-discharging power of the EVG should not exceed the corresponding upper limitation because the EVG output is a stochastic variable that should meet the following constraint:

$$\Pr \{ 0 \leq g_{EV,t}^{chr} \leq \bar{g}_{EV,t}^{chr} \} \geq \beta_2 \quad (27)$$

$$\Pr \{ 0 \leq g_{EV,t}^{dis} \leq \bar{g}_{EV,t}^{dis} \} \geq \beta_3 \quad (28)$$

(4) DR operation constraint

DR implementation can change customer behavior and transfer / curtail part of the load demand. This part of the load demand is regarded as virtual generation units, which have similar constraints to those of

CPP operation. The primary constraints include the maximum curtailment load constraint, climbing constraint and minimum startup-shutdown time constraint.

- **Load curtailment constraint**

To ensure the basic load demand, the curtailment load provided by DR should not exceed the maximum value:

$$|L_t - L_t^0| \leq \Delta L_t^{\max} \quad (29)$$

$$\Pr\{0 \leq \Delta L_t^P \leq s_t^P \Delta \bar{L}_t^P\} \geq \beta_4 \quad (30)$$

$$\Pr\{0 \leq \Delta L_t^I \leq s_t^I \Delta \bar{L}_t^I\} \geq \beta_5 \quad (31)$$

- **Load climbing constraint**

To realize peak-valley shifting, the load change generated by PBDR and IBDR should meet the climbing constraints:

$$s_t^P L_D^P \leq \Delta L_t^P - \Delta L_{t-1}^P \leq s_t^P L_U^P \quad (32)$$

$$s_t^I L_D^I \leq \Delta L_t^I - \Delta L_{t-1}^I \leq s_t^I L_U^I \quad (33)$$

wherein s_t^P and s_t^I are the operation states of PBDR and IBDR, respectively, and are both 0-1 variables.

1 indicates operation, and 0 indicates shutdown.

- **Startup-shutdown time constraint**

After receiving the price change signal and corresponding instructions from the ISO, customers need some time to adjust their power consumption behaviors. In addition, the load provided by PBDR and IBDR should also meet the startup-shutdown time constraints:

$$\left[X_{t-1}^{P,on} - T^{P,on} \right] (s_{t-1}^P - s_t^P) \geq 0 \quad (34)$$

$$\left[X_t^{P,off} - T^{P,off} \right] (s_t^P - s_{t-1}^P) \geq 0 \quad (35)$$

$$\left[X_{t-1}^{I,on} - T^{I,on} \right] (s_{t-1}^I - s_t^I) \geq 0 \quad (36)$$

$$\left[X_t^{I,off} - T^{I,off} \right] (s_t^I - s_{t-1}^I) \geq 0 \quad (37)$$

- **Operation situation constraint**

To increase the convenience for the ISO with regard to making the scheduling scheme based on customer demand response, customers should choose to participate in PBDR or IBDR. Thus, one customer cannot participate in both PBDR and IBDR at the same time:

$$s_t^P \cdot s_t^I = 0 \quad (38)$$

In addition, to ensure stable load demand, customer demand response times of IBDR should meet:

$$\sum_{t=1}^T (s_t^{I,u} + s_t^{I,d}) \leq S^{I,\max} \quad (39)$$

(6) System reserve constraint

$$\Pr\{G_t^{VPP,\max} - G_t^{VPP} + \Delta L_t^P + \Delta L_t^I \geq \bar{R}_t^{VPP}\} \geq \beta_6 \quad (40)$$

$$\Pr\{G_t^{VPP} - G_t^{VPP,\min} \geq \underline{R}_t^{VPP}\} \geq \beta_7 \quad (41)$$

$$R_t^{VPP} = r_1 \cdot L_t + r_2 \cdot g_{W,t} + r_3 \cdot g_{PV,t} + r_4 \cdot g_{EV,t} \quad (42)$$

Customer upstream spinning reserve indicates customers reducing power consumption to increase power generation. Customer downstream spinning reserve indicates customers increasing power consumption to reduce power generation.

In the above model, the objective function $\bar{f}_3$, Eq. (21)-(24) and Eq. (34)-(37) are non-linear objective functions and non-linear constraints, respectively. Therefore, to reduce the difficulty of solving the model, the solving method of [40] is applied to linearize the objective functions and constraints.

4 Three-Stage Hybrid Intelligent Solution Algorithm

The VPP scheduling model is characterized by multiple constraints, multiple variables and non-linearity. Generally, traditional optimization solution methods are slow and have poor convergence, which make them not able to address large-scale calculations in VPP scheduling problems. Swarm intelligent algorithms refer to biological group-evolution processes that search for the optimal solution, which can overcome the insufficiency of traditional algorithms. Therefore, this study puts forward a three-stage hybrid intelligent algorithm to solve the proposed model. In the first stage, an improved particle swarm algorithm with stochastic imitate technology and cloud evolve thought (SC-PSO) is built to solve the optimization model with a single objective function. In the second stage, a decision attribute table of objective functions is calculated with the results of the single objective models. Then, the entropy weight method is used to obtain the weight of each objective. In the third stage, the model decision-making method is constructed with the fuzzy satisfaction theory (SFT-Decision Making Method) to calculate the satisfactory optimization result.

4.1 First-stage: SC-PSO Algorithm

4.1.1 Particle swarm algorithm

Particle swarm optimization (PSO) was put forward by Kennedy and Eberhart in 1995. The PSO algorithm initializes a particle swarm and adjusts its search direction and position to gain the optimal solution by learning from the individual extreme value and the global value to find the optimal solution.

During the search progress, the particles adjust their search direction and speed and update their position to find the optimal particle. PSO has four characteristics: (1) each particle is initialized with a stochastic velocity and moves in the entire problem space, (2) each individual has a memory function, (3) individual evolution is primarily realized by cooperation and competition between individuals, and (4) PSO is a simple method and has a deep intelligence background. A detailed introduction of PSO is presented in [41].

4.1.2 Cloud evolve thought

Particle fitness changes greatly due to the uncertainty output of the VPP and DR. The majority of the particles are of a low fitness level, which makes it more difficult for the particles to efficiently find the optimal solution. Therefore, PSO cannot exceed its limitations and is liable to fall into local optima, known as ‘early-maturing.’ During the search progress, the optimal solution and other solutions are not completely separated but have a continuous relationship, i.e., they obey a stealth law. Cloud evolve thought could aid in building the uncertainly model to transfer a qualitative concept into a quantitative value by finding this stealth law [42]. Cloud evolve generates a normally distributed cloud swarm around the excellent cloud droplets and improves the proportion of excellent cloud droplets via iteration and updating. Therefore, cloud evolve thought can involve early-maturing and identify the global optimal.

The definition of a cloud is as follows: assume that U is a quantitative discussion domain represented by an accurate numeral. C is a qualitative concept on U , and for any element x of the discussion domain, x is a random implementation of the qualitative concept C . The certainty degree of x is $\beta(x) \rightarrow [0,1]$, a random variable with a stable trend.

$$\beta: U \rightarrow [0,1] \quad X \rightarrow \beta(x) \quad (43)$$

The overall concept feature of the cloud model can be reflected by digital features of the cloud. The expected value E_x , the entropy E_n and the hyper entropy H_e can represent a cloud. Using three numbers to describe the overall characteristic of the concept, written as $C(E_x, E_n, H_e)$, the detailed calculation method and cloud evolve search method is introduced in [43]. This study introduces cloud evolve thought into particle swarm optimization and chooses excellent particles according to the fitness calculation result. Then, a vector is constructed by those excellent particles, and the vectors construct an evolve cloud. Fig. 2 shows the particle distribution of the cloud evolve model.

Fig. 2 Particle distribution of the cloud evolutionary model

4.1.3 Stochastic simulation technology

There are two ways to solve the stochastic chance constraint planning. (1) Transform the chance constraint planning into determined planning to solve the problem by determined planning theory. However, some constraints are difficult to transfer. (2) Address the chance constraints with stochastic imitate technology and then solve the problem with an intelligent algorithm [43]. This study chooses the second method to address the stochastic constraints.

$$\Pr(g_j(x, \xi) \leq 0, j = 1, 2, \dots, m) \geq \beta_j \quad (44)$$

For an unconditional variable x , set $N_1=0$ and then generate N random variables according to the PDF.

If the random variable ξ and the decision variable x meet the inequality $g_j(x, \xi) \leq 0, j = 1, 2, \dots, m$, then increment N_1 by 1. When N is large enough, Eq. (44) comes into play according to the big-number law; thus, $N_1/N \geq \beta_j$. Conversely, if $N_1/N < \beta_j$, the passed particle would not meet the confidence level of Eq. (44), indicating that the particle should be abandoned and replaced by a new particle until all particles meet the constraint of $N_1/N \geq \beta_j$.

4.2 Second-stage: Function Weight Model

Based on the SC-PSO algorithm described in Section 4.1, this study sets $\bar{f}_i (i=1, 2, \dots, k)$ as the optimization objectives for obtaining the solution set. The decision attribute table of the objective functions

is listed in Table 1.

Table 1 The decision attribute table of objective functions

Function	$\bar{f}_1$	$\bar{f}_2$	...	$\bar{f}_k$
$\bar{f}_1^*$	r_{11}	r_{12}	...	r_{1k}
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
$\bar{f}_k^*$	r_{1k}	r_{k2}	...	r_{kk}

Annotation: * denotes setting the objective as the optimization objective and solving the model.

According to the decision attribute table, the decision matrix of the objectives can be obtained as $[r_{ij}]_{k \times k}$ ($i, j = 1, 2, \dots, k$). Both cost-objective and benefit-objective exist in the objective set. Different objectives have different orders of magnitude, which require a pre-handle before weighting the objectives. The detailed handle method is as follows.

- For cost-objective, they should be handled by Eq. (45):

$$r'_{ij} = \frac{\max_i r_{ij} - r_{ij}}{\max_i r_{ij} - \min_i r_{ij}}, j = 1, 2, \dots, k \quad (45)$$

- For benefit-objective, they should be handled by Eq. (46):

$$r'_{ij} = \frac{r_{ij} - \min_i r_{ij}}{\max_i r_{ij} - \min_i r_{ij}}, j = 1, 2, \dots, k \quad (46)$$

After Eq. (45) and Eq. (46), the decision matrix after the pre-handle $[r'_{ij}]_{k \times k}$ can be obtained. Then, the entropy weight method is introduced to solve the weights of the objectives [10]:

- Calculate the entropy E_i of objective $\bar{f}_i$:

$$E_i = -\psi \sum_{j=1}^n r_{ij} \ln(r'_{ij}), i = 1, 2, \dots, k \quad (47)$$

wherein $\psi = 1/\ln(n)$, a constant related to the sample number, to make $E_i \in [0, 1]$, r'_{ij} satisfies

$0 < r'_{ij} < 1$ and $\sum_{j=1}^n r'_{ij} = 1$, and when $r_{ij} = 0$, $r_{ij} \ln(r'_{ij}) = 0$.

- Calculate the weights of the objective functions:

$$d_i = 1 - E_i, i = 1, 2, \dots, k \quad (48)$$

$$\lambda_i = \frac{d_i}{\sum_{i=1}^k d_i}, i = 1, 2, \dots, k \quad (49)$$

Then, the weights of the single objectives with their weight coefficients are used to synthesize the objective function as follows:

$$\begin{cases} \max \tilde{f} \\ s.t. \Pr\{\tilde{f} \geq \bar{f}\} \geq \min\{\alpha_i\} \\ \tilde{f} = \sum_{i=1}^k \lambda_i \bar{f}_i' \\ i = 1, 2, 3 \end{cases} \quad (50)$$

wherein $\bar{f}_i^r$ is the objective function that is obtained from Eqs. (45)-(46).

Then, Eq. (50) is set as the optimization objective function with the constraints from Eq. (19) through Eq. (42). The SC-PSO algorithm is used to solve the model and obtain the global optimal solution set.

4.3 Third-stage: SFT- Decision Making Method

The method in section 4.1 and section 4.2 could obtain a global optimal solution set considering all objectives, namely the Pareto optimal frontier. Then, the decision-maker needs to choose the best compromise solution according to the specific preferences for different applications. The fuzzy satisfaction method is introduced to build the decision-making method [44]. The membership function of objective function i in Pareto optimization scheme r is defined as u_i^r . The drop-gradient membership function is introduced to address the cost-objective, and the ascending half-line membership function is introduced to address the benefit-objective, as follows:

$$u_n^r = \begin{cases} 1, & \bar{f}_n^r \leq \min(\bar{f}_n) \\ \frac{\max(\bar{f}_n) - \bar{f}_n^r}{\max(\bar{f}_n) - \min(\bar{f}_n)}, & \min(\bar{f}_n) \leq \bar{f}_n^r \leq \max(\bar{f}_n), n = 1, 2, \dots, k \\ 0, & \bar{f}_n^r \geq \max(\bar{f}_n) \end{cases} \quad (52)$$

$$u_m^r = \begin{cases} 1, & \bar{f}_m^r \geq \max(\bar{f}_m) \\ \frac{\bar{f}_m^r - f_3^{\min}}{f_3^{\max} - f^{\min}}, & \min(\bar{f}_m) \leq \bar{f}_m^r \leq \max(\bar{f}_m), m \neq n, m = 1, 2, \dots, k \\ 0, & \bar{f}_m^r \leq \min(\bar{f}_m) \end{cases} \quad (53)$$

$$u^r = \frac{\sum_{i=1}^k \lambda_i \cdot u_i^r}{\sum_{r=1}^R \sum_{i=1}^k \lambda_i \cdot u_i^r} \quad (54)$$

wherein m and n are the indexes of the objective function, $i=n+m$, r is the index for the Pareto solution set, R is the Pareto solution set, and $\bar{f}_i^r$ and u_i^r are the objective values $\bar{f}_i^r$ and its membership degree value Pareto optimization scheme r , respectively. The solution with the maximum membership function is the most preferred compromise solution based on the adopted weight factors, which is also selected as the best Pareto-optimal solution or the final solution of the optimization problem. Fig. 3 shows the three-stage hybrid intelligent solution algorithm flow chart.

5 Case Study

To verify the validity and applicability of the proposed model, this section constructs the simulation

scenario set. Then, the *Yunnan* distributed power demonstration engineering project in China is taken as the simulation object for example analysis.

Fig. 3 Three-stage hybrid intelligent solution algorithm flow chart

5.1 Scenario set

Case 1: The basic scenario, VPP scheduling without the EVG and DR. This scenario did not consider the EVG and DR but analyzed the applicability of the proposed stochastic scheduling model and corresponding algorithm in overcoming the uncertainty factors of VPP operation.

Case 2: EVG scenario, VPP scheduling with only the EVG. This scenario only considers VPP

scheduling with the EVG, assuming all EVs are plug-in electric vehicles. The charging-discharging power and the total charging capacity of EVs are 1.8 kW and 10.8 kW·h. The energy loss rate of the charging-discharging power is 5.6%. The number of EVs is 1000 [45]. Assume that the charging-discharging power deviation of the EVG obeys the normal distribution $N(0,0.12^2)$ [38]. The charging-discharging power price of the EVG follows the TOU price [8].

Case 3: DR scenario, VPP scheduling with only DR. This scenario considers the VPP scheduling scheme with PBDR and IBDR. Assume that the electric price before PBDR is 590 Yuan/MW·h. Referring to [34], this study sets the electric price at a load peak, float and valley period and demand-price elasticity. Table 2 contains the time-of-use period and price parameters. To avoid peak-valley upside-down, this case limits the fluctuation load of PBDR to not more than 15% of the original load, namely 3 MW.

Table 2 Time-of-use period and price parameters

Parameter	Price with PBDR/(Yuan/MW·h)		
Period	Valley Period	Normal Period	Peak Period
	0:00-5:00,21:00-24:00	5:00-8:00,14:00-19:00	8:00-14:00,19:00-21:00
Price	260	590	920

For IBDR, the upstream/downstream spinning reserve price is 800 Yuan/MW·h and 160 Yuan/MW·h [10]. The maximum load and load fluctuation of IBDR participating in spinning reserve is not more than 3.5 MW and 1.5 MW.

Case 4: Comprehensive scenario, VPP scheduling with the EVG and DR. This scenario considers scheduling schemes with both the EVG and DR. The detailed parameters are the same as in the other cases.

5.2 Basic data

China's *Yunnan* distributed power demonstration engineering project is taken as the simulation object [45]. The project includes a 4.5MW PV, a 6.5MW WPP and 18 MW hydro power units in *Xiaozhongdian*, *Shuoduogang* river. Similar to hydro units, the CPP has rapid startup-shutdown speeds and low pollutant emission levels. Therefore, this study selects the CPP to replace hydro units with a similar installed capacity. The CPP contains one TAURUS60, one CENTAUR50 and one CENTAUR40 gas turbine [46] and divides the cost curve into two segments to linearize it. The detailed parameters are listed in Table 3.

Table 3 CPP operation parameters

Unit type	$g_{CPP}^{\min}$ /MW	$g_{CPP}^{\max}$ /MW	$\Delta g_{CPP}^{\pm}$ /MW	$D_{CPP,t}$ /Yuan	$M_{CPP}^{\text{on/off}}$ /h	Slope of segment 1 /(Yuan/MW)	Slope of segment 2 /(Yuan/MW)
TAURUS60	2.5	5.67	3	204.8	2	239	273.2
CENTAUR50	2	4.6	2.5	136.3	1.5	150.25	307.3
CENTAUR40	1	3.515	1.8	122.9	1	136.6	341.5

This engineering project was built to meet the demand load in *Diqing*, *Yunnan* province. Its typical

demand load curve is described in [45]. The minimum values of the daily minimum demand load rate in *Diqing* are 57% in March. The prices of the WPP and PV are set by the government as 610 Yuan/MW·h and 1000 Yuan/MW·h, respectively [45]. According to [47], the price of the CPP is set as 560 Yuan/MW·h. In addition, historical data of wind velocity and illumination intensity in *Diqing* were selected for the regression fitting of the probability density functions [45]. The parameters of the wind turbine are $v_{in} = 3\text{ m/s}$, $v_{rated} = 14\text{ m/s}$ and $v_{out} = 25\text{ m/s}$, and the shape parameter and scale parameter are $\varphi = 2$ and $g = 2\bar{v}/\sqrt{\pi}$ [10], respectively. The values of α and β are 0.32 and 8.14, respectively. The method proposed by [48] is used to simulate the generation scenarios of the WPP and PV. 10 typical scenarios are obtained, with the mean value of all scenarios taken as the input value. The details are shown in Fig. 4.

Fig. 4 Predicted values (24 h) for load, WPP and PV

The initial population size is set to 2000, the learning factor $c_1=c_2=0.2$, the maximum inertia weight $w_{max}=0.8$, the minimum inertia weight $w_{min}=0.8$, the maximum flight speed $V^{max}=10$, and the maximum iteration number is 2000 [40]. During the cloud evolve search process, five excellent particles are chosen according to their fitness values. In addition, five particle swarms are generated around those five particles by using the cloud evolve search method. The optimal confidence is when the error of the two continuous generations is within the allowed range [44]. MATLAB 2011a was used as the solving software on an Ideapad-Y450 computer with a 3.4-GHz CPU and 4 GB RAM.

5.3 Example results

5.3.1 Case 1: VPP scheduling without EVG and DR

The March load with the maximum load rate is selected as the basic data to study the application of stochastic constraint planning in overcoming the inner uncertainty of the WPP and PV. Assuming that the prediction error of VPP power generation is 10%, the electricity-cut compensation cost is 1.2 Yuan/kW·h.

The confidence parameters of α and β are 0.9 and 0.92, respectively. Using the proposed algorithm to solve the models with and without uncertainty, the time to solve the model is 70 s and 78 s, which are less than the solution times in the basic PSO algorithm (95 s and 102 s) and the non-dominated sorting genetic-II (NSGA-II) algorithm (85 s and 97 s) [49]. The computational time for the other three cases are 85 s, 88 s and 95 s. Table 4 is the decision attribute table of the objective functions.

Table 4 The decision attribute table of the objective functions (unit: Yuan)

	Without uncertainty			With uncertainty		
	$\bar{f}_1$	$\bar{f}_2$	$\bar{f}_3$	$\bar{f}_1$	$\bar{f}_2$	$\bar{f}_3$
$\bar{f}_1^*$	18395.23	9819.60	180711.17	7132.84	16232.79	177529.76
$\bar{f}_2^*$	18910.30	9645.56	183128.09	7353.96	15806.03	180443.07
$\bar{f}_3^*$	19719.69	9780.60	185916.84	7475.22	16311.82	182081.81

Compared with the objective function value without uncertainty, the system operation cost is reduced from 183.95 million to 71.33 million Yuan when the uncertainty is considered. However, the system abandoned energy cost would increase, which indicates that the grid connection power and operation income of the VPP are reduced. To reduce the electricity shortage cost due to the VPP output uncertainty, system scheduling would reduce the power output of the WPP and PV. Based on the decision attribute table (Table 3), to analyze the VPP output structure with and without uncertainty, this study used the entropy weight method (Eq. (44)-Eq. (54)) to weight multiple objective functions and make the optimal decision. Then, the VPP operation scheduling is obtained as shown in Fig. 5(Schedule 1).

Fig. 5 The scheduling result comparison of the VPP in Case 1 with (a) and without uncertainty (b)
 If considering uncertainty, the power output of the WPP and PV would decrease, whereas the CPP output would increase. The abandoned power of the WPP and PV increased from 9.90 MW·h to 15.82 MW·h and 3.61 MW·h to 6.15 MW·h, respectively. The grid connection power of the CPP increased from 310.61 MW·h to 319.55 MW·h. To reduce the power shortage cost due to the VPP uncertainty, the system would reduce the output of the WPP and PV and increase the CPP output to meet the load demand.

Finally, set $\alpha = \beta$ to analyze the influence of the confidence level on system scheduling. The objective values and VPP grid connection power under different confidence levels are obtained by the sensitivity analysis. The detailed results are listed in Table 5.

Table 5 System scheduling results under different confidence levels

(α, β)	Objective value /Yuan			VPP grid connection /MW·h
	$\bar{f}_1$	$\bar{f}_2$	$\bar{f}_3$	
0.8	7548.24	15028.18	188245.39	464.21
0.84	7391.56	15335.26	186012.48	461.32
0.88	7273.45	15548.27	183585.19	458.57
0.92	7132.84	15806.03	182081.81	455.29
0.96	6937.95	16028.45	179587.60	452.08

As the confidence degree increases, the decision-maker's willingness to bear the power shortage cost will decrease. The VPP grid connection power decreased from 464.21 MW·h to 452.08 MW·h. The abandoned energy cost and system operation cost increase, but the VPP scheduling income decreases. That is, the stochastic change constraint planning method can effectively control the uncertainty of the VPP

output. The system power shortage costs and VPP operation risk will decrease, which could provide a prevention and control tool for the decision-maker.

5.3.2 Case 2: VPP scheduling with only EVG

This section discusses the EVG's optimization effect on VPP scheduling. The parameter values are similar to those in Case 1. Then, the optimization result shows that the system operation cost, abandoned energy cost and VPP operation income are 6599.91 Yuan, 12222.41 Yuan and 184563.1 Yuan, respectively. According to the simulation results, the EVG can only alleviate the influence of uncertainty on system power generation. However, compared with Case 1, the system operation cost and abandoned energy cost are markedly reduced, whereas the VPP operation income is increased. The output of the WPP and PV increased by 2.97 MW·h and 0.94MW·h, respectively. Fig. 6 is the scheduling results of VPP in Case 2.

Fig. 6 The scheduling results of the VPP in Case 2

In Case 2, the VPP consists of a WPP, PV, CPP and EVG. The EVG and CPP both provide reserve services for the WPP and PV. Compared with Case 1, the system operation cost decreases and VPP operation income increases. The EVG could substitute the CPP to provide reserve service. Therefore, the CPP output decreased from 319.55 MW·h to 316.28 MW·h. In particular, during the period from 1:00-8:00, the CPP output decreased by 45.27 MW·h. The EVG charging-discharging distribution with 1000 EVs (benchmark value) is shown in Fig.7(Schedule 2)

Fig. 7 Electric vehicle charging-discharging distribution

According to Fig. 7, the EVG primarily charges power during the valley periods and discharges power during the peak periods. Some EVs charge power while others discharge power during flat periods. This shows that the EV charging-discharging time distribution is opposite the demand load distribution. Furthermore, sensitivity analysis was performed to analyze the influence of the EVG grid connection number on the load demand and VPP grid connection power. The sensitivity analysis results is shown in Fig.8(Schedule 3).

Fig. 8 Sensitivity analysis results for the electric vehicle number in Case 3

According to Fig. 8, with an increase in the number of EVG grid connections, the load demand curve

becomes smoother. When the number reaches 2000, the peak load and valley load are 25.31 MW and 16.45 MW, respectively. The peak-valley ratio is 1.59. Compared with the original results, the peak load decreased by 560 kW, the valley load increased by 1.01 MW, and the peak-valley ratio decreased by 0.16. Regarding the GC output power, the system generally reduces the power purchasing from the GC, which indicates that the system power shortage is alleviated. Therefore, the VPP could make use of the EVG to meet the load demand with EV charging power during the valley load periods and discharging power during the peak load periods.

5.3.3 Case 3: VPP scheduling with only DR

This section analyzes the influence of PBDR and IBDR on VPP generation scheduling. The parameter values are the same as in Case 1. The simulation results show that the system operation cost, abandoned energy cost and VPP operation income are 7836.48 Yuan, 7415.78 Yuan and 186368.45 Yuan, respectively. DR could help smooth the load demand curve, improve the VPP grid connection, decrease the abandoned energy cost and increase the VPP operation income. However, DR also expanded the uncertainty influences of the WPP and PV on system power generation. Compared with Case 1, the system operation cost increases by 703.56 Yuan. The load demand curve before and after PBDR and IBDR is shown in Fig.9.

Fig. 9 Load demand curve before and after PBDR and IBDR

According to Fig. 9, both PBDR and IBDR show good peak-valley shifting effects. Compared with the original load demand curve, the peak-valley ratio of the load demand curves after PBDR and IBDR are 1.57 and 1.55, respectively. IBDR has a more obvious peak-valley shifting effect on the load demand curve. For PBDR, customer responses lag behind the TOU price. Therefore, some load will also shift and increase during the float load period. For IBDR, the load demand is almost constant during the float period. Therefore, the load demand curve after IBDR is smoother than that after PBDR. When both PBDR and

IBDR are introduced, the load demand curve is smoothed to the maximum extent. The peak load is 25.31 MW, the valley load is 16.39 MW, and the peak-valley ratio is 1.54. The optimization result of VPP scheduling in Case 3 is shown in Fig.10 (Schedule 4).

Fig. 10 the optimization result of VPP scheduling in Case 3

Compared with Fig. 5, the load demand curve considering DR is smoother. The WPP grid connection power increased by 3.46 MW·h, the PV grid connection power increased by 1.67 MW·h, the CPP output decreased by 4.45 MW·h. According to the IBDR load distribution, customers provide positive output (load) to consume the VPP power output during the valley load periods. In addition, customers provide negative output (curtailment load) to reduce the CPP output to provide more reserve service capacity for the WPP and PV during the peak load periods.

5.3.4 Case 4: VPP scheduling with EVG and DR

This section discusses the optimization effect with both EVG and DR. The parameter values are the same as in the above scenarios. The simulation result shows that the system operation cost, abandoned energy cost and VPP operation income are 6990.46 Yuan, 5691.58 Yuan and 188307.53 Yuan, respectively. Therefore, when both EVG and DR are introduced, the system operation result is optimized, which not only makes use of the EVG charging-discharging capacity to provide reserve service for the WPP and PV but also smoothes the load demand curve to expand the VPP grid connection space. Compared with Case 3, the EVG alleviates the uncertainty influence of the VPP output on system scheduling and reduces the system operation cost. Compared with Case 2, PBDR could smooth the load demand curve, and IBDR provides reserve service for the VPP from the demand side, which maximizes the VPP grid connection power. The load demand distribution for the four cases is shown in Fig.11 (Schedule 5).

Fig. 11 Load demand distribution in the four cases

According to Fig. 11, when both EVG and DR are introduced, the load demand is smoothed to the maximum extent. In Case 4, the peak load and the valley load are 24.85 MW and 17.02 MW, respectively. Compared with Case 1, the peak-valley ratio decreased from 1.74 to 1.46, reaching the minimum point, which indicates that the EVG and DR have a coordinated optimization effect. The EVG provides reserve service for the VPP on the generation side. DR smoothes the load demand on the demand side to improve the VPP grid connection. In this manner, a chain reaction between the generation side and demand side is created. The VPP scheduling optimization result in Case 4 is shown in Fig.12 (Schedule 6).

Fig. 12 VPP scheduling optimization result in Case 4

Compared with the other cases, the VPP grid connection power reaches a maximum in Case 4. The outputs of the WPP, PV and CPP are 96.32 MW·h, 46.16 MW·h and 314.79 MW·h, respectively. Compared with Case 1, the WPP output increased by 5.43 MW·h, and the PV output increased by 2.6 MW·h, whereas the CPP output decreased by 4.76 MW·h. The EVG could substitute the CPP to provide reserve service for the VPP by charging or discharging power. In addition, the IBDR output would be reduced, which indicates that the EVG can reduce the system reserve cost. The VPP power output in the

four cases is shown in Fig.13(Schedule 7).

Fig. 13 VPP power output in the four cases

According to Fig. 13, the VPP outputs in the four scenarios are 453.525 MW·h, 455.65 MW·h, 456.68 MW·h and 458.83 MW·h, respectively. Compared with Case 1, the EVG can output in the peak load periods and consume power in the valley load periods in Case 2, which makes the peak-valley ratio of the VPP output curve larger than the original curve, e.g., 1:00~5:00 and 9:00~15:00. In addition, compared with Case 1, DR could smooth the load demand curve in Case 3. The load in the peak load period decreased, and the load in the valley load period increased. The VPP output power distribution curve is identical to the load demand curve. In Case 4, both the EVG and DR are incorporated. The VPP output combined its characteristics in Case 2 and Case 3, namely, the VPP output curve is smoother, and the grid connection power reaches the maximum. Table 6 shows the optimization scheduling results of the four scenarios.

Table 6 The optimized system operation results for the four cases

	Object function value			VPP power output/MW·h					DR/MW					Peak-valley ratio
	$\bar{f}_1$	$\bar{f}_2$	$\bar{f}_3$	WPP	PV	CPP	EVG		IBDR		PBDR			
							charge	discharge	Up	Down	peak	flat	valley	
Case1	7132	15806	182081	90.89	43.56	319.55	—	—	—	—	—	—	—	1.74
Case2	6600	12222	184563	93.86	44.50	316.28	15.29	13.76	—	—	—	—	—	1.59
Case3	7836	7416	186368	94.35	45.23	315.10	—	—	-16.33	10.53	-7.90	-0.12	2.96	1.54
Case4	6990	5692	188307	96.32	46.16	314.79	12.23	11.01	-14.83	8.59	-3.27	0.75	4.27	1.46

According to Table 6, compared with the other three cases, the scheduling scheme is optimal in Case 4.

For the objective values, compared with Case 2, the system operation cost increased, the system abandoned energy cost decreased, and the VPP operation income was optimized, which indicate that the system operation result reached the optimal level. The VPP power generation reached the maximum of 458.83MW·h, which is more than the 453.525 MW·h in Case 1. For the peak-valley ratio, the EVG, IBDR and PBDR have the same effect on peak-valley shifting. The peak load decreased by 1.36 MW, the valley

load increased by 1.93 MW, and the peak-valley ratio reached the minimum of 1.46. For the VPP output structure, the EVG replaced the CPP to provide reserve service. Compared with Case 1 and Case 2, the CPP output in Case 4 decreased by 1.49 MW and 4.76 MW, respectively. For the DR implementation effect, the EVG helps overcome the VPP output uncertainty, which alleviates the pressure on DR. Therefore, the PBDR and IBDR outputs were less than those in Case 2.

6 Conclusions

In this study, a WPP, PV, EVG and CPP are aggregated in a VPP. Stochastic chance constraint planning is introduced to overcome the uncertainties of VPP scheduling. Then, a stochastic scheduling model for the VPP is proposed with the objective functions of minimum system compensation cost, minimum abandoned energy cost and maximum VPP operation income. Then, a three-stage hybrid intelligent solution algorithm is developed to solve the proposed model using the particle swarm algorithm, the entropy weight method and the fuzzy satisfaction theory. The simulation results show:

(1) If considering uncertainties, the system will reduce the VPP power generation and decrease the power shortage cost. This could control the influence of the uncertainty of the WPP and PV on system operation. The grid connection power of the VPP will decrease more with a higher confidence level. That is, stochastic chance constraint planning can be applied to overcome VPP uncertainties and provide risk control tools for decision-makers.

(2) The proposed three-stage hybrid intelligent solution algorithm could obtain the optimal decision solution of the VPP scheduling model. The cloud evolve thought is introduced into the traditional particle swarm algorithm by using the cloud evolve model to update the excellent particles. Stochastic simulation technology could prevent the early maturation problem and obtain the global optimal particles. The entropy weight method and the fuzzy satisfaction theory could solve the weight coefficients of the objective functions and obtain the optimal decision solution of the multi-objective model.

(3) The system operation cost and abandoned energy cost will reach minimum values and the VPP operation income will reach a maximum value when the EVG and DR are both introduced. The EVG could replace the CPP output to provide spinning reserve service for the WPP and PV and ensure the stability of VPP output. DR can smooth the demand load curve, expand the VPP grid connection space and achieve linkage optimization of the generation side and demand side.

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Appendix

Schedule 1 the scheduling result comparison of VPP in Case 1(unit: MW·h) (Fig.5)

	With uncertainty			Without uncertainty				With uncertainty			Without uncertainty		
	WPP	PV	CPP	WPP	PV	CPP		WPP	PV	CPP	WPP	PV	CPP
1	4.199	0	13.79	4.199	0	13.79	13	3.9	4.008	12.582	3.9	5	11.536
2	3.325	0	13.79	5.499	0	11.494	14	3.302	4.401	13.79	3.302	4.401	13.79
3	2.795	0	13.79	4.998	0	11.463	15	3.497	4	13.79	3.497	4	13.79
4	4.372	0	11.29	4.467	0	11.19	16	3.302	3.402	13.79	3.302	3.402	13.79
5	4.467	0	11.19	4.659	0	10.987	17	2.697	2.3	13.79	2.697	2.3	13.79
6	4.727	0	11.19	4.797	1.318	9.725	18	3.003	2.3	13.79	3.003	2.3	13.79
7	3.926	1.506	11.29	4.199	1.741	10.754	19	3.601	1.399	13.79	3.601	1.399	13.79
8	2.6	2.241	13.79	2.6	2.241	13.79	20	3.998	0.999	13.79	3.998	0.999	13.79
9	3.9	3.501	13.79	3.9	3.501	13.79	21	4.699	0	13.79	4.699	0	13.79
10	3.626	4.198	13.79	4.199	4.198	13.185	22	3.9	0	13.79	3.9	0	13.79
11	3.802	4.5	13.79	3.802	4.5	13.79	23	4.498	0	13.79	4.498	0	13.79
12	3.553	4.801	13.79	3.9	4.801	13.424	24	5.2	0	13.79	5.2	0	13.79

Schedule 2 the scheduling result comparison of VPP in Case 1(Fig.7)

Charge power			Discharge power			Charge power			Discharge power		
1	1000	0	9	0	1000	17	497.2	502.8			
2	1000	0	10	0	1000	18	400	600			
3	1000	0	11	0	1000	19	0	1000			
4	1000	0	12	0	1000	20	0	1000			
5	1000	0	13	0	1000	21	0	1000			
6	700	300	14	260	740	22	800	200			
7	600	400	15	400	600	23	1000	0			
8	400	600	16	600	400	24	1000	0			

Schedule 3 sensitive analysis results for electric vehicle number in Case 3 (unit: MW·h)(Fig.8)

	None	1000	1200	1400	1600	1800	2000		None	1000	1200	1400	1600	1800	2000
1	18	19.8	20.16	20.52	20.88	21.24	21.6	13	19.85	19.24	19.05	18.85	18.45	18.23	18.05
2	16.41	18.21	18.57	18.93	19.29	19.65	20.01	14	20.91	20.12	19.962	19.804	19.646	19.488	19.33
3	15.88	17.68	18.04	18.4	18.76	19.12	19.48	15	20.65	20.35	20.29	20.23	20.17	20.11	20.05
4	15.09	16.89	17.25	17.61	17.97	18.33	18.69	16	20.91	21.31	21.39	21.47	21.55	21.63	21.71
5	15.09	16.89	17.25	17.61	17.97	18.33	18.69	17	23.82	23.86	23.87	23.88	23.88	23.89	23.9
6	15.35	16.1	16.25	16.4	16.55	16.7	16.85	18	25.12	24.82	24.76	24.7	24.64	24.58	24.52
7	16.15	16.55	16.63	16.71	16.79	16.87	16.95	19	24.88	23.18	22.84	22.5	22.16	21.82	21.48
8	19.59	19.29	19.23	19.17	19.11	19.05	18.99	20	25.94	24.24	23.9	23.56	23.22	22.88	22.54
9	21.97	20.27	19.93	19.59	19.25	18.91	18.57	21	26.21	24.51	24.17	23.83	23.49	23.15	22.81
10	20.91	19.21	18.87	18.53	18.19	17.85	17.51	22	25.15	24.85	24.79	24.73	24.67	24.61	24.55
11	22.24	20.54	20.2	19.86	19.52	19.18	18.84	23	21.71	23.51	23.87	24.23	24.59	24.95	25.31
12	21.44	19.74	19.4	19.06	18.72	18.38	18.04	24	20.65	22.45	22.81	23.17	23.53	23.89	24.25

Schedule 4 the optimization result of VPP scheduling in Case 3 (unit: MW·h) (Fig.10)

	WPP	PV	CPP	IBDR		WPP	PV	CPP	IBDR		WPP	PV	CPP	IBDR
1	4.199	0	13.79	2.65	9	3.9	3.501	13.79	-2.5	17	2.697	2.3	13.79	0
2	4.135	0	13.79	2.87	10	3.535	4.198	13.2	-2.5	18	3.003	2.3	13.79	-0.08
3	3.709	0	13.69	2.9	11	3.802	4.5	13.79	-2.6	19	3.601	1.399	13.79	-2.43
4	5.417	0	11.19	3.16	12	3.9	4.801	12.69	-2.6	20	3.998	0.999	13.79	-3.42
5	4.557	0	11.19	1.44	13	3.9	5	12.26	-1.3	21	4.699	0	13.79	-2.33
6	4.797	1.095	11.19	1.1	14	3.302	4.401	13.55	-1.26	22	3.9	0	13.79	-0.11
7	4.199	1.093	11.29	0	15	3.497	4	13.79	0	23	4.498	0	13.79	3.14
8	2.6	2.241	13.79	-0.2	16	3.302	3.402	13.79	0	24	5.2	0	13.79	3.07

Schedule 5 load demand distribution in four cases (unit: MW·h) (Fig.11)

	Case 1	Case 2	Case 3	Case 4		Case 1	Case 2	Case 3	Case 4
1	18	19.8	20.5	20.84	13	19.85	18.15	18.84	18.14
2	16.41	18.56	19.02	19.85	14	20.91	20.12	19.77	18.94
3	15.88	17.71	18.5	19.21	15	20.65	20.35	20.46	20.16
4	15.09	16.91	17.84	19.08	16	20.91	21.31	21.17	21.57
5	15.09	16.89	16.98	18.12	17	23.82	23.86	23.85	23.89
6	15.35	16.1	16.39	17.14	18	25.12	24.82	24.89	24.31
7	16.15	16.55	16.41	17.02	19	24.88	23.18	22.56	22.86
8	19.59	19.29	19.3	19	20	25.94	24.24	23.62	23.12
9	21.97	20.27	19.62	18.56	21	26.21	24.51	23.94	23.24
10	20.91	19.21	18.56	18.45	22	25.15	25.65	25.31	23.93
11	22.24	20.54	19.84	18.86	23	21.71	23.73	24.21	24.85
12	21.44	19.74	19.04	19.12	24	20.65	22.45	23.36	23.68

Schedule 6 VPP scheduling optimization result in Case 4(unit: MW·h) (Fig.12)

	WPP	PV	CPP	EVG	IBDR		WPP	PV	CPP	EVG	IBDR
1	4.2	0	13.79	-1.8	1.4	13	3.9	5	11.53	1.7	-0.35
2	5.5	0	13.23	-1.8	2	14	3.3	4.4	12.67	0.79	-1.34
3	4.33	0	13.78	-1.8	1.89	15	3.5	4	13.66	0.3	-0.26
4	4.2	0	13.79	-1.8	2.55	16	3.3	3.4	13.79	-0.4	0.34
5	5.1	0.45	11.35	-1.8	1.59	17	2.7	2.3	13.79	-0.04	0.03
6	4.8	0.97	11.19	-0.75	1.19	18	3	2.3	13.79	0.3	-0.57
7	4.2	1.7	11.29	-0.4	0.55	19	3.6	1.4	13.79	1.7	-0.66
8	2.6	2.24	13.79	0.3	-0.35	20	4	1	13.79	1.7	-1.46
9	3.9	3.5	13.55	1.7	-2.05	21	4.7	0	13.79	1.7	-1.61
10	4.2	4.2	12.38	1.7	-1.1	22	3.9	0	13.79	-1.1	-2.1
11	3.8	4.5	12.92	1.7	-2.02	23	4.5	0	13.79	-1.8	1.7
12	3.9	4.8	12.77	1.7	-0.96	24	5.2	0	13.79	-1.8	1.59

Schedule 7 VPP power output in four cases (unit: MW·h) (Fig.13)

	Case 1	Case 2	Case 3	Case 4		Case 1	Case 2	Case 3	Case 4
1	17.989	16.099	17.99	16.85	13	20.436	23.955	21.16	22.125
2	16.993	15.372	17.93	16.55	14	21.493	22.283	21.25	21.165
3	16.461	14.261	17.4	16.12	15	21.287	21.587	21.29	21.457
4	15.657	12.452	16.61	15.24	16	20.494	20.094	20.49	20.094
5	15.646	12.886	15.75	15.12	17	18.787	18.744	18.79	18.7468
6	15.84	14.437	17.08	15.78	18	19.093	19.393	19.09	19.593
7	16.694	15.961	16.58	16.792	19	18.79	20.49	18.79	20.49
8	18.631	18.931	18.63	18.931	20	18.787	20.487	18.79	20.487
9	21.191	22.891	21.19	22.652	21	18.489	20.189	18.49	20.189
10	21.582	23.887	20.93	22.48	22	17.69	17.59	17.69	16.81
11	22.092	23.792	22.09	22.918	23	18.288	17.488	18.29	17.188
12	22.125	24.191	21.39	23.17	24	18.99	18.19	18.96	17.89

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