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Optimal Scheduling of Virtual Power Plant with Risk Management

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Abstract

Due to intense electricity consumption, environmental concerns and technological development, a great number of renewable distributed resources have been widely installed in the distributed network. However, the reality that renewable distributed resources frequently fluctuate under high penetration makes effective use a challenge. Fortunately, with improved communication architecture and control techniques, this could be achieved by a Virtual Power Plant (VPP). VPP can aggregate various resources in a distributed generation portfolio, by creating one single operating profile. The aim of this paper is mainly to analyze optimal scheduling of VPP to maximize its profit, with due consideration given to the uncertainty of renewable energy output, such as wind power, and to make the energy mix respond to system need. A risk quantization method (CVaR) is introduced to deal with uncertainty. This paper presents a VPP scheduling model, which takes VPP total operation cost, traded electricity cost, unit earnings, supply-demand balancing and other constraints into account, with a CVaR assessment method embedded into this model. According to the scenarios generated by uncertainty of wind power output, numerical results for a proposed case are discussed. These results show the expected profit of VPP scheduling is closely associated with different degrees of confidence , which is a great help for VPP operators when making the tradeoff between risk and profit.

Keywords: Distributed generation; Virtual Power Plant (VPP); Conditional value at risk (CVaR); Uncertainty; Profit;

1. Introduction

Along with the implementation of increasingly stringent environmental protection laws and regulations in every country, and the continued upward pressure on environmental issues, people are increasingly inclined to choose clean, environmentally friendly and renewable energy systems, of which perhaps the most attractive is the development of distributed energy resources (DERs). DERs usually include distributed generation, which refers to the micro hydroturbine, micro wind turbine, photovoltaic power generation and micro gas turbine, energy storage system, and temperature controlled load on the demand side. DER will play a very important role in the future energy structure, as it can not only provide clean energy supply and improve energy efficiency, but also reduce emissions of greenhouse gases caused by the large number of conventional fossil fuel generating units [1–4]. Since DERs are usually directly installed on the user side of the distribution network instead of connecting to the main grid, this makes the power flow in the distribution network display the characteristic of bidirectional flow. Although theoretically the total generating capacity of DERs can replace conventional generators, because of natural conditions and cost control DERs cannot provide the necessary ancillary service support for the main grid when a critical situation occurs on the system side. If DERs are not managed effectively, it will increase investment cost and sharply increase system operation cost, which af-

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fects the absorption of DERs by the system in return [5–7] To achieve free and flexible access in the distribution system for DERs, the concept of a Virtual Power Plant (VPP) was proposed. VPP can gather together all DERs in a given region through advanced internal communication and control architecture, delivering effective management of large-scale, decentralized DERs [8–10], and make various different DERs' operating parameters generate an external unified operating profile, which means the VPP can represent all DERs when participating in the electricity market and offer bidding to the main grid. VPP can provide high reliability, high quality, high security and always available power service for the system, making the management of a large number of DERs more efficient and thereby enhancing the stability of system operation. Generally speaking, VPP has the three following major characteristics: (1) VPP emphasizes the "wide area" characteristics, which means power generation equipment in VPP has very wide spatial distribution, however, VPP does not own any power plant entities and cannot form a power plant entity like conventional power plants [11]; (2) the main application for VPP is to integrate renewable energy and demand side resources, so the power output of integration can show a similar or identical technical feature to conventional power plants, for example, providing an upper and lower limit of output, operation cost curve, reserve capacity, ramp rate, frequency and voltage profile to dispatch center [12]; (3) the assets in VPP are not necessarily owned by the VPP generation company. The relationship between the VPP generation company and DERs is the scheduling of the energy flow, the allocation of currency flow and the share of information flow, which is very much akin to the relationship between the traditional power grid dispatch center, trading center and power plant [13]. However, due to the uncertainty of the output power of the wind turbine, photovoltaic and other renewable distributed generation, and the uncertainty of the electricity price, the VPP needs to consider the risk caused by uncertainty when the VPP makes its scheduling decision. So, a method is proposed to deal with the risk caused by uncertainty in VPP scheduling. For example, Ernan Ni [14] applied the algorithm of combined Lagrangian relaxation and stochastic dynamic programming to solve the daily market optimization formulation of a generation company (Genco) under risk management in the deregulated power industry, which significantly reduced revenue variances and Genco's bidding risk. To cope with the uncertainty caused by short-term wind power output, Xiaohu Li [15] used VaR(Value at Risk) to quantify the risk caused by wind power, and took the VaR as the penalty factor into the short-term operation model of hybrid power system, which showed that the expected value of system operation cost played a very important role in risk management, and encouraged power suppliers to make a more accurate forecast of wind power with a view to gaining more revenue. For the acquisition of optimal spinning reserve under large wind power penetration, Junli Wu [16] proposed a kind of cost-CVaR model to deal with load forecast error and deviations of wind power, by analyzing various risk levels, and the desired tradeoff between profit and risk was made. This paper proposes conditional value at risk (CVaR) to analyze the impact of a various unit output portfolio on the VPP overall scheduling cost in light of the uncertainty of wind power output, to maximize the expected profit assuming a given risk level which reflected the imbalance in VPP scheduling. This paper is organized as follows. Section 2 introduces the composition of VPP, the internal control strategy and market frame. Section 3 describes the proposed risk management method. Section 4 presents the VPP scheduling cost formulation under the risk of deviation of wind power. Section 5 describes the case study. And finally, Section 6 concludes the main findings of this work.

2. VPP Description

2.1. VPP Components

The typical structure of a VPP is shown in Fig.1. As shown in Fig.1, VPP includes a micro combined heat and power generation unit (αCHP), micro wind turbine, photovoltaic (PV), micro conventional distributed generation, storage system (including energy and heat), and a certain amount of demand side resources (controllable load). VPP gathers together varieties of distributed power generation, through advanced communication technology and software management, forming a whole controllable power generation system. Because of the power output fluctuation of wind turbine and PV, VPP needs to trade energy with an external distribution network. When the power output of VPP surpasses the internal load demand, VPP can make an electricity transaction to an upstream network by offering a certain amount of ancillary services, which is P_{exp} in Fig. 1. When the internal power of VPP is insufficient to meet the load profile, VPP can make a purchase of electricity from the grid by a virtual tie line, which is P_{imp} in Fig.1.

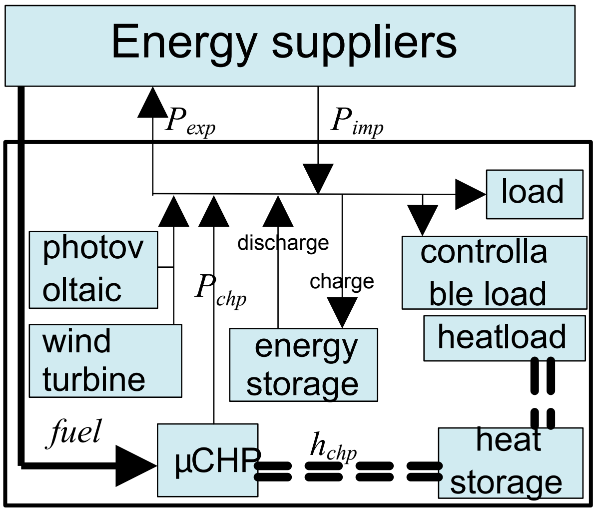

Figure 1: The Structure of VPP

2.2. Internal control strategy of VPP

There are two types of control mode for the management of VPP, centralized control and dispersed control [17]. Centralized control mode [18] provides a top-down approach to managing distributed generation in the region. In this mode, the distributed generation units are directly controlled by a control coordination center (CCC) and all distributed generation units transmit system load demand signals to CCC. After these signals are processed by algorithm in CCC, distributed generation controllers (DGC) which are near the distributed generation units will receive unit relevant information such as power generation scheduling, unit start-stop status and so on, then the units will operate as the signal instructed. This control architecture allows CCC to put into effect the management plan of distributed generation. When there is enough or insufficient electricity in VPP, CCC carries out the electricity sale or purchase to gain extra profit or meet the load profile by the virtual tie line of VPP-grid. This kind of mode means CCC can execute the technical and economic functions of VPP to obtain the maximum benefit in the energy and reserve market of the grid through bidding. While in decentralized control mode, VPP usually uses hierarchical control architecture to govern distributed generation [19], which mainly includes two major control layers, the lower layer and the high layer. In the lower level control, various DERs are managed by the local controller (LC), and DGs are controlled by LC with a logical algorithm. To develop an integrated system, each LC is connected one after another to form a circle structure, and the information is mutual exchanged, then the lower layer transmits the information which it assembled to the high layer control center. The high layer control center will coordinate the power output of various distributed generation. In this paper, VPP is presumed to be centrally controlled and aims to maximize the total profit of VPP.

2.3. Power market framework of VPP

As Figure 1 showed, VPP plays two roles in the electric power market trading: utilizing the balance market with bidding and offering for balancing the load profile of VPP like every other conventional generator. First, VPP will forecast the next 24 hours load demand and energy price levels through historical data, then CCC in the VPP calculates the generation scheduling of each distributed generation according to power capacity, ramp rate, unit operation status and other unit parameters, and submits it to each distributed generation, allowing distributed generation to bid in the day ahead power market of system. If there is a shortage of electricity or an electricity surplus in VPP, VPP can engage in real-time energy exchange with the grid by the virtual tie line.

3. Problem formulation

3.1. Risk measure (CVaR)

When X is represented as an invest portfolio vector, random vector $Y \in R^m$ (R^m is represented as m dimensional real space) denotes random factors in the market, the loss function of X can be denoted by $f(x, y)$. If the joint probability density function of Y is $p(Y)$, for a certain value of X, the probability value caused by Y which does not exceed critical value (α represented a certain level of loss) can be expressed by:

$$\psi(X, \alpha) = \int_{f(x,y)\leq\alpha} p(Y)dY \tag{1}$$

in the expression, $X \in \Omega$, Ω is a subset of n dimensional real space R^n, Ω denotes a feasible solution of the portfolio.$\psi(X, \alpha)$ is the loss of cumulative distribution function under X. If the confidence level of loss function $f(x, y)$ caused by Y is β, which is no more than α, then $\alpha_\beta(X)$ and $\phi_\beta(X)$ can denote the value at risk(VaR), CVaR of the loss function of X, respectively. $\alpha_\beta(X)$ and $\phi_\beta(X)$ can be calculated by:

$$\alpha_\beta(X) = \min\{\alpha \in R : \psi(X, \alpha) \geq \beta\} \tag{2}$$

$$\phi_\beta(X) = \frac{1}{1-\beta}\int\limits_{f(X,Y)\geq\alpha_\beta(X)} f(X,Y)p(Y)dY \tag{3}$$

in (3), $\phi_\beta(X)$ is the CVaR when loss is greater than $\alpha_\beta(X)$. Because it is very difficult to obtain the analytical expression of $\alpha_\beta(X)$, the transformation function$F_\beta(X,\alpha)$ is introduced to replace $\phi_\beta(X)$ to simplify the calculation of CVaR:

$$F_\beta(X,\alpha) = \alpha + \frac{1}{1-\beta}\int\limits_{Y\in R^m} (f(X,Y)-\alpha)^+ p(Y)dY \tag{4}$$

Because Rockafekkar and Uryasev [20] proved that $F_\beta(X,\alpha)$ is a convex and continuous function regarding α, so CVaR can be obtained by minimizing$F_\beta(X,\alpha)$:

$$CVaR = \min_{x\in X,\alpha} F_\beta(X,\alpha) \tag{5}$$

in (4),$(f(X,Y)-\alpha)^+$ denotes the maximum value of $\{f(X,Y)-\alpha, 0\}$, which can use historical data of Y or the Monte Carlo simulation method to estimate the integral term of (4). If $Y_1, Y_2 \ldots Y_N$ are the sample data, the estimate value of $F_\beta(x,\alpha)$is:

$$\hat{F}_\beta(X,\alpha) = \alpha + \frac{1}{N_c(1-\beta)}\sum_{k=1}^{N}(f(X,Y_k)-\alpha)^+ \tag{6}$$

3.2. Uncertainty modeling of renewable energy generation output

VPP contains a large number of renewable distributed generation units, such as wind turbines and photovoltaic units. The output of these units was limited by wind speed or illumination intensity because of typical stochastic characteristics, resulting in uncertainty of the overall output of VPP. So renewable energy generation modeling is necessarily required. To assume that the upper limit and the lower limit of the output of wind turbine or photovoltaic in one scheduling period are$\bar{P}_R^S$ and $\underline{P}_R^S$, the reference value of output is$\widetilde{P_R}(t)$ and the variance value is $\varepsilon(t)$, then the outputs uncertainty of wind turbine or photovoltaic units in VPP can be described as follows:

$$\left\{P_R(t) = \widetilde{P}_R(t) + \varepsilon(t); \underline{\varepsilon} \leq \varepsilon(t) \leq \bar{\varepsilon}; \underline{P}_R^S \leq \sum_{t=1}^{24} P_R(t) \leq \bar{P}_R^S\right\} \tag{7}$$

3.3. VPP total cost function modeling

VPP total cost function (TCF) includes the start-up cost and operation cost of distributed generation:

$$\begin{aligned} C_{TCF} = &\sum_{i\in S_{ds}, t=1:24} \left(C_{dg,i,t}(P_{dg,i,t}\cdot I_{i,t}) + SC_{dg,i,t}\cdot J_{i,t}\right) \\ &+ \sum_{k\in S_{str}} C_{str,k,t}(P_{str,k,t}) \end{aligned} \tag{8}$$

3.4. Traded electricity cost of VPP- grid

Due to the fluctuation characteristics of renewable distribution generation outputs in VPP and the absence of large capacity conventional generating units in it, when there is a power shortage or surplus in VPP, VPP will make the electricity transactions with the main grid though a virtual tie line to meet the load profile, so traded electricity cost can be stated as follows:

$$J = \sum_{t=1}^{24}\left[-\alpha_t x_\alpha(t) - \beta_t x_\beta(t)\right] P_m(t) \tag{9}$$

in (9), $x_\alpha(t)$) and $x_\beta(t)$ are state variable of power purchase and power selling of VPP in T time interval, respectively. When $P_m(t) < 0$,$x_\alpha(t) = 1$, or when $P_m(t) > 0$, $x_\beta(t) = 1$, which are restrained:

$$\begin{cases} x_k(t) = \{0,1\}, k = \alpha, or, \beta \\ \\ x_\alpha(t) + x_\beta(t) \leq 1 \end{cases} \tag{10}$$

3.5. Objective function

In this paper, we assume that the outputs of distributed generation will be settled with a unified price in the energy market, and the uncertainty outputs of the wind turbines lead to different levels of income fluctuations of VPP in the energy market, showing certain risk characteristics, causing power producers in VPP to take a different risk attitude during the transaction, which leads to significant differences in market revenue. This paper defined the negative earnings of VPP as the loss function, and presented an operation optimization model under risk, physical and network constraints:

$$\min\{\alpha + \frac{1}{N_C(1-\beta)}\sum_{i=1}^{N_C}\left[\sum_{i=1}^{N_G} C_{TCF} + \sum_{i=1}^{T} J - \lambda\sum_{i=1}^{N_G} P_G - \alpha\right]^+\} \tag{11}$$

In (11), N_C is the sample number of wind output, which is generated by Monte Carlo simulation, λ is retail electricity price, and P_G is the total output of distributed generation in VPP.

This paper uses u_i to denote $(\sum_{i=1}^{N_G} C_{TCF} + \sum_{i=1}^{T} J - \lambda \sum_{i=1}^{N_G} P_G - \alpha)$,so (11) can be transformed into linear programming, which is subject to : $u_i \leq 0$

Constraints:

Outputs range and ramp rate of distributed generation:

$$\begin{cases} P_{dg,i}^{\min} \leq P_{dg,i} \cdot I_{i,t} + R_{dg,i,t} \cdot I_{i,t} \leq P_{dg,i}^{\max} \\ R_{i,t} I_{i,t} \leq \min\left\{10 \times MSR_i, P_{dg,i}^{max} - P_{dg,i,t}\right\} \end{cases} \tag{12}$$

Outputs range of storage system:

$$-\left(cap_{0,i} - P_{str,i}^{\min}\right) \leq \sum_{t=1}^{24} P_{str,i,t} \leq P_{str,j}^{\max} - cap_{0,i} \tag{13}$$

Power balance equation in VPP under the condition of neglect of network loss:

$$P_m(t) + \sum_{i \in S_{dg}} P_{dg,j,t} + \sum_{j \in S_{dg}} P_{curt,j,t} + \eta_{str} \sum_{i \in S_{str}} P_{str,i,j} = LOAD \tag{14}$$

4. Case study

The aim of this paper is to develop an optimal scheduling model of VPP, which could make the VPP company determine the profit-risk tradeoff by CVaR efficient frontier, offering an easily understood way of making decisions. The case study provides a numerical example, which has eight distributed generation units. DG1, DG3, DG6 and DG7 are conventional distributed units. DG2 and DG5 are micro wind turbines, whose rated power is 100KW, cut-in speed is 3m/s, rated speed is 10m/s, and cut-out speed is 25m/s. DG4 and DG8 are storage systems. The output of DG2 and DG5 will be simulated in section 4.2, and other parameters of units and VPP load profile are shown in Fig.2 and Fig.3, respectively. This model has been solved by CPLEX package in Matlab, using a computer with a 2.5GHz Celeron processor and 2GB RAM.

4.1. Wind output data

Due to the uncertainty output of the wind turbine which was described in (8), a scenario tree is usually proposed to model the decision-making process under

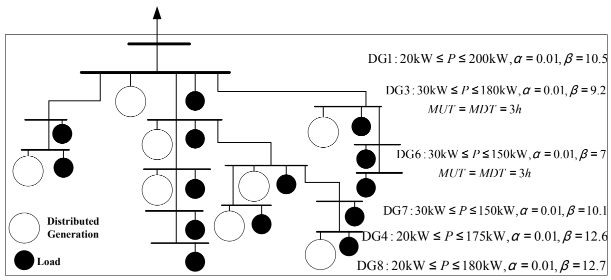

Figure 2: VPP single line diagram

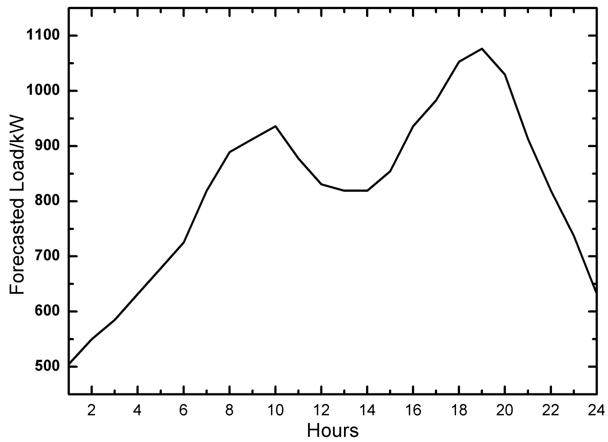

Figure 3: Load profile in VPP

the uncertainty, each node can represent a point where the decision is made, and each branch is the expression form of output status. The first node is called the root node where the first stage decision is made, and the node in the final stage is called the leaf. The number of leaves is the number of scenarios [21]. This paper uses the ARIMA method to generate 500 scenarios of wind power outputs, which can approximately represent the distribution of wind power production over the day. Because it is impossible to calculate the risk value of VPP operation using so many scenarios, a technique of scenario reduction is required to select the most typical subset of scenarios to cover all the information. So the fast-forward reduction algorithm in Ref.[22]is used to obtain the reduced sets by minimizing the probability distance to the original sets with continuous iterative. The time horizon chosen in this paper is 24 hours, the generated wind power output scenarios is 10, and the probability of each scenario is 0.1,and wind power output scenarios were shown in Fig. 4.

4.2. Result analysis

Fig.5 clearly shows the extent to which the fluctuation of wind turbine output can affect the profit of the Virtual Power Plant. As Fig.5 shows, at hour 9, hour

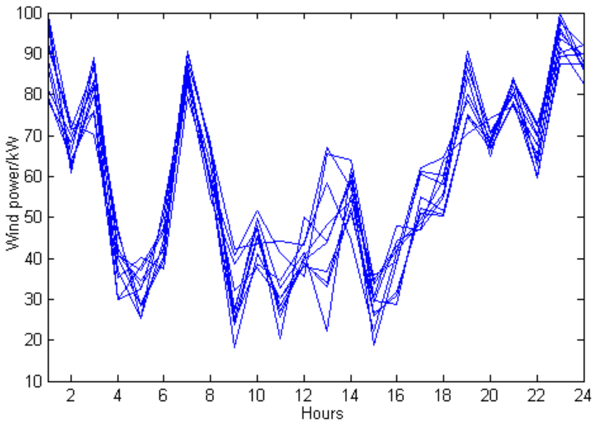

Figure 4: Wind power output scenarios

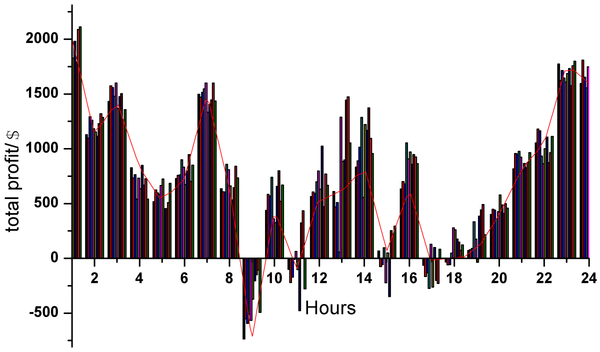

Figure 5: Profit distribution under scenarios (β=0.95)

11, hour 13 and hour 17, the total profit of VPP is negative, because the wind power output is lower at the same time interval in one day and the load demand is in rising-trend. This means that VPP has to purchase a large amount of electricity from the main grid during the peak demand of load profile. Furthermore, we can also see another 3 typical time intervals, hour 1, hour 9 and hour 19. At hour 1, the wind turbine is almost close to maximum output, 100kW, but load demand is at its lowest, which leads to VPP selling the surplus electricity to the main grid to expand earnings, and the mean profit at hour 1 in 10 scenarios is 2022.20$. At hour 9, VPP has to purchase 102.73kW electricity from the main grid, although the quantity of electricity purchased is not the most in one day, but due to the maximum load demand in daytime and the shortage of wind output, this makes units in VPP operate at maximum capability, which means the profit of VPP cannot cover total cost, causing the total profit of VPP in one day to fall to its maximum negative value, -428.90$. At hour 19, load demand is at its highest for the whole day, even though the wind power output is nearly 90kW, the average profit is only 224.57$.

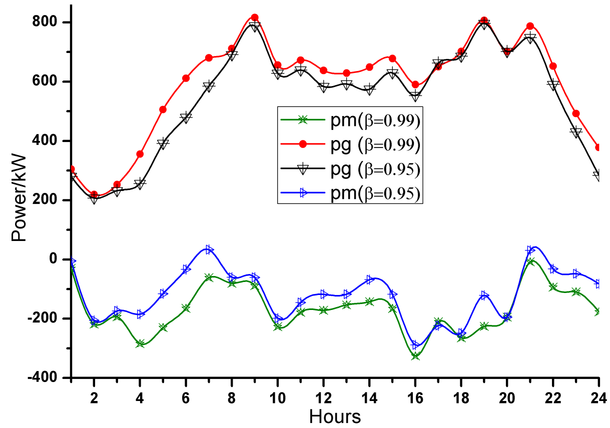

Figure 6: Unit output at a different degree of confidence within the lower boundary of wind power output

Since each scenario is equally likely to occur, this paper analyzes VPP operation in two extreme scenarios at degree of confidence 0.95 and 0.99, which are the upper and lower boundaries of wind turbine output, as shown in Fig.6 and Fig.7.

In Fig.6, pm and pg denote traded electricity and total unit output in VPP, respectively. As we can see, at the lower degree of confidence ($\beta = 0.95$), VPP operator will ignore the risk of wind power fluctuations, utilizing most of the wind energy, which reduces the conventional distributed generation in VPP. But at the higher degree of confidence ($\beta = 0.99$), VPP limit the absorption of wind power to reduce the fluctuation, making much greater use of conventional distributed generation, so VPP has to purchase more electricity from the main grid. Since the cost of traded electricity is a small proportion of total cost, even if the amount of traded electricity at the higher degree of confidence increases to 43.99%, the profit of VPP at the higher degree of confidence still adds up to 20.12%.

In Fig.7, purchasing the energy from the network for VPP at the higher confidence ($\beta = 0.99$) will increase to 47.82% than the amount for VPP at the lower degre of confidence ($\beta = 0.95$), which is greater than the purchase amount of electricity in Fig.6 for bigger wind power volatility, but the profit is still 16.78% more than VPP's at the lower degree of confidence ($\beta = 0.95$).

Fig.8 demonstrates the expected profit of VPP versus standard profit at a different degree of confidence . Since each scenario has the same probability of occurrence, this enables us to derive the efficient frontier, which can provide the VPP operator with the risk-preference curve to make the tradeoff between expected profit and risk. As we also can see from Fig.8,

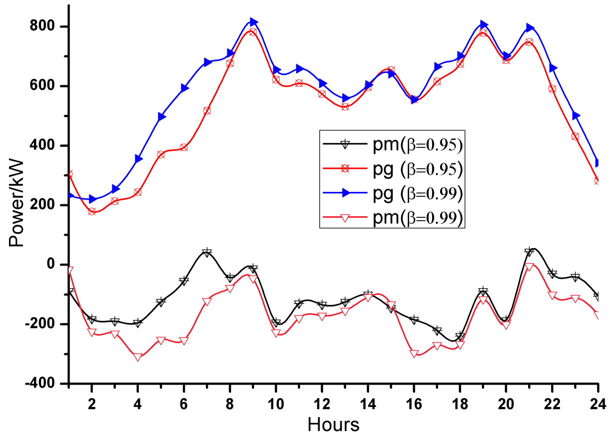

Figure 7: Unit output at a different degree of confidence within the higher boundary of wind power output

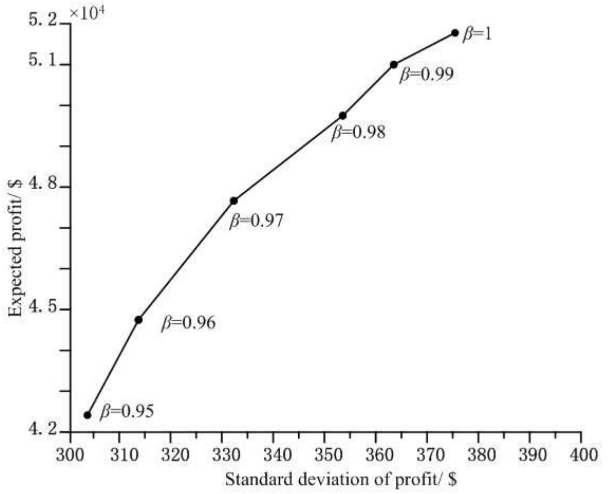

Figure 8: Expected profit versus standard deviation at a different degree of confidence

with the increment of β, the expected profit will grow gradually to the maximum achievable risk level.

5. Conclusion

In this paper, optimal scheduling of VPP has been formulated and studied. Since the fluctuation of wind turbine output poses a risk to VPP scheduling, the risk was taken into account when building the VPP scheduling objective function. Firstly, typical scenarios of wind power output were generated using the ARIMA method and scenarios reduction was applied to produce 10 wind output scenarios. A scheduling objective function was then imbedded into the CVaR assessment according the definition of loss function. An example simulation was conducted and a thorough comparison at different degrees of confidence presented, illustrating the efficient frontier to determine the tradeoff between expected profit and risk.

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