Optimal dispatch of multi-virtual power plants based on Grey Wolf Optimization algorithm

Yingliang Li*, Liwen Zhou, Zhaodi Gao, Kun He, Heming Cai, Xiyao Sun
School of Electronic Engineering, Xi’an Shiyou University, 710065, Xi’an, Shaanxi, China
Corresponding author: yingliang.li@xsyu.edu.cn

Abstract. The day-ahead scheduling of virtual power plant (VPP) is of great significance for the development of distributed generations. To solve the problem of large-scale VPP scheduling, this paper proposes a multi-VPPs optimal dispatching strategy. In this model, the VPP is divided into multiple sub-VPPs, and each sub-VPP scheduled internally. Likewise, the power interaction between each sub-VPP at the contract price is allowed. This model can realize complementary power, and hence maximize economic benefit of VPP and also improve the level of new energy consumption. Then, to solve this nonlinear optimization problem, Grey Wolf Optimization (GWO) algorithm is employed. Finally, the proposed model is tested through a detailed case study, and results demonstrate that the GWO algorithm can improve the computational efficiency.

1. Introduction
With the fast increasing demand of electricity, distributed generations (DGs) represented by wind power generations and photovoltaic generations are developing rapidly [1-2]. To solve the problem of Renewable Energy Sources power output intermittency and fluctuations, virtual power plant (VPP) was proposed [3-4].

Based on the distributed power management system, VPP aggregates distributed power, controllable loads, energy storage devices and others into a virtual controllable aggregate, and then participates in the operation and dispatching of the grid as a whole to maximize the economic and environmental benefits. It is also an effective method for distributed energy resources (DER) to join the electricity market [5-6].

At present, researchers have carried out a lot of studies on the problem of VPP optimization dispatching, most of which are the research on the internal optimization dispatching of a single VPP, and a few articles launch the research on the optimization scheduling of multiple VPPs. Literature [7] established a multi-VPPs control architecture based on a multi-agent system, which can improve system revenue through transactions between multiple virtual power plants. Literature [8] combined with renewable energy, considered the electricity trading between multiple virtual power plants, and proposed an optimal scheduling strategy for multiple virtual power plants, which saved the VPP power purchase cost and improved the overall revenue. Literature [9] established a virtual power plant collaborative scheduling model by scenario analysing based on cooperative game theory. But this article did not consider demand response. Literature [10] proposed a point-to-point energy interaction mechanism. At the bottom layer, each VPP dispatched its internal distributed energy, and at the top layer, each VPP negotiated trade prices and quantities. The aforementioned documents have conducted certain researches on the optimal scheduling of multiple VPPs, but the demand response module is only a simple
application and has not been studied. The existing demand response model is relatively complicated and needs to be analyzed according to specific issues.

The above analysis shows that the existing VPP optimal scheduling problem mainly focuses on the single-VPP scheduling strategy, and there is little research involved in the multi-VPPs optimal scheduling strategy. This paper takes VPP, aggregated of wind turbines, photovoltaics, diesel generators, and demand response, as an example. In the context of time-of-use electricity prices, a multi-VPPs optimal scheduling model is established that considers the power interaction between VPPs and takes into account the user's demand response willingness. VPP has the lowest power generation cost and the largest demand response utility as the objective function. The Grey Wolf Optimization (GWO) algorithm is used to solve the model. Finally, the correctness of the model is verified through the analysis of a numerical example.

2. Problem Formulation

2.1 Objective function

The objective of this work is to minimize the comprehensive operating cost within the VPP, which consists of generation cost and demand response cost. The objective function can be defined as follows:

1) Generation cost:

\[
F_{VPP} = F_{VPP1} + ... + F_{VPPn} = \sum_{i=1}^{24} \sum_{t=1}^{n} (a_{i,n}Pc_{i,t}^2 + b_{i,n}Pc_{i,t}) + \sum_{i=1}^{24} (\lambda_{i,j}Pg_{i,t}) + \sum_{i=1}^{24} (\lambda_{i,j}Ptr_{i,t})
\]

where, \(F_{VPPn}\) is the cost of VPPn, \(C(Pc)\), \(C(Pg)\) and \(C(Ptr)\) are the cost of conventional generators, interaction costs with the grids, transaction costs with the sub-VPPs respectively. \(a_{i,n}\) and \(b_{i,n}\) are the fuel cost coefficients, \(Pc_{i,t}\) is the output power of unit i at time t in VPPn. \(Pg_{i,t}\) and \(Ptr_{i,t}\) are the transfer power between grids and VPPs respectively. \(\lambda_{i,j}\) and \(\lambda_{i,j}\) are the prices of electricity market and VPP contract.

2) Demand response cost:

\[
\max F_2 = \sum_{i=1}^{24} (\lambda_{i,j}x_{i,t} - h_{i,j})
\]

where, \(\lambda_{i,j}\) is the “value of power interruptibility” of DR i at time t, and is also the Locational Marginal Price which can be calculated via optimal power flow. \(x_{i,t}\) is the quantity of power reduced by DR i at time t, and \(h_{i,j}\) is the allowance which VPP pay to response customers.

3) Objective function of VPP:

\[
\min F = \min w_1F_1 + w_2(-F_2)
\]

where, \(w_1\), \(w_2\) are weight coefficient, and \(w_1 + w_2 = 1\).

2.2 Constraint equations

1) Power balance constraints:

\[
P_{W_{i,t}} + P_{S_{i,t}} + P_{G_{i,t}} + P_{C_{i,t}} + P_{Tr_{i,t}} = L_{i,t} + D_{i,t}
\]

where, n is VPPn, and t represents time t. \(P_{W_{i,t}}\) is the power of wind generator. \(P_{S_{i,t}}\) is the power of solar generator. \(P_{G_{i,t}}\) is the power interaction between VPP and grid. \(P_{C_{i,t}}\) is the power of conventional generators. \(P_{Tr_{i,t}}\) is the interaction power between VPPs. \(L_{i,t}\) is the load. \(D_{i,t}\) is the reduced power of DR.
2) The conventional generator output constraints:
\[ P_{c,t} = \sum_{i} P_{c_{i,t}} \]  
(6)
\[ p_{c_{t},\text{min}} \leq P_{c_{i,t}} \leq p_{c_{t},\text{max}} \]  
(7)
\[ p_{d_{i,t}} \leq P_{c_{i,t+1}} - P_{c_{i,t}} \leq p_{u_{i}} \]  
(8)
where, \( P_{c_{i,t}} \) is the power of generator \( i \) at time \( t \) in VPP. \( p_{c_{t},\text{min}} \) and \( p_{c_{t},\text{max}} \) are the minimum and maximum power of conventional generator \( i \) respectively. \( p_{d_{i}} \) and \( p_{u_{i}} \) are the ramp down and up rates of conventional generator \( i \).

3) Demand response constraints:
\[ D_{n,t} = \sum_{i} x_{i,t} \]  
(9)
\[ x_{i,\text{min}} \leq x_{i,t} \leq x_{i,\text{max}} \]  
(10)
\[ \sum_{j=1}^{n} x_{j,t} \leq D_{L_{i}} \]  
(11)
where, \( x_{i,\text{min}} \) and \( x_{i,\text{max}} \) are the minimum and maximum curtailed power of DR \( i \) respectively. \( D_{L_{i}} \) is the daily limit load of DR \( i \).

4) Power interaction constraints:
\[ P_{tr_{\text{min}}} \leq P_{tr_{n,t}} \leq P_{tr_{\text{max}}} \]  
(12)
\[ P_{s_{\text{min}}} \leq P_{s_{n,t}} \leq P_{s_{\text{max}}} \]  
(13)
where, \( P_{tr_{\text{min}}} \) and \( P_{tr_{\text{max}}} \) are the minimum and maximum interaction power between VPPs respectively. \( P_{s_{\text{min}}} \) and \( P_{s_{\text{max}}} \) are the minimum and maximum interaction power between VPP and grid respectively.

5) Wind and solar output constraints:
\[ 0 \leq P_{w_{n,t}} \leq P_{w_{\text{max}}} \]  
(14)
\[ 0 \leq P_{s_{n,t}} \leq P_{s_{\text{max}}} \]  
(15)
where, \( P_{w_{\text{max}}} \) and \( P_{s_{\text{max}}} \) are the maximum power of wind and solar generator respectively.

3. Solution Approach
The Grey Wolf Optimization algorithm is a stochastic optimization algorithm based on the predation behavior of wolves in nature. And it was proposed by Mirjalili et al in 2014 [11]. The algorithm is simple to use and effectively solves the difficulty of parameter debugging in traditional swarm intelligence algorithms [12].

3.1 The principle of GWO
The mathematical model of Grey Wolf Optimization algorithm is mainly constructed from the hierarchy, encircling and attacking prey of grey wolves. The wolf group is divided into \( \alpha \), \( \beta \), \( \delta \) and \( \omega \) wolf according to the grades. The \( \alpha \) wolf is the leader, who decides the rest and hunting time of the whole wolf group and plays a decision-making role. The \( \beta \) wolf is second in the pack's hierarchy of priorities. They help the leader wolf \( \alpha \) make decisions. The \( \delta \) wolf must follow and obey the wolf \( \alpha \) and the wolf \( \beta \). The wolf of the lowest rank is called wolf \( \omega \), and the wolf \( \omega \) must obey all the wolves except himself. The position of prey can correspond to the optimal solution in the optimization problem.

Enclosure: The encirclement strategy of grey wolf is determined by the following two formulas [11]:
\[ D = | C \cdot X_{p}(t) - X(t) | \]  
(16)
\[ X(t+1) = X_{p}(t) - A \cdot D \]  
(17)
where, \( t \) is the number of iterations, \( A \) and \( C \) are the coefficient vectors, \( X_{p} \) represents the position vector of prey, and \( X \) represents the position vector of grey wolf.
The vector \( A \) and \( C \) can be calculated by the following formula [13]:

\[
\begin{align*}
A &= 2a \cdot r_1 - a \\
C &= 2 \cdot r_2
\end{align*}
\]

where, \( a \) is a convergence factor, decreases from 2 to 0 as the number of iterations increases, \( r_1 \) and \( r_2 \) are random number in \([0,1]\).

Hunting: When the prey has ceased, the wolf attacks the prey. Prey can be regarded as the objective function obtained from a practical problem. The general assumption is that the \( \alpha \) wolf (the best candidate solution), the \( \beta \) wolf and \( \delta \) wolf master the possible location of prey and these are the first three optimal solutions to obtain the optimal solution so far. The remaining solutions are known as the \( \omega \) wolf, and they will update their positions based on the positions of \( \alpha \), \( \beta \), and \( \delta \) wolf. The mathematical expression of the predation process of grey wolves is as follows [14]:

\[
\begin{align*}
D_\alpha &= |C_1 \cdot X_\alpha - X| \\
D_\beta &= |C_2 \cdot X_\beta - X| \\
D_\delta &= |C_3 \cdot X_\delta - X| \\
X_1 &= X_\alpha - A_1 \cdot (D_\alpha) \\
X_2 &= X_\beta - A_2 \cdot (D_\beta) \\
X_3 &= X_\delta - A_3 \cdot (D_\delta) \\
X(t+1) &= \frac{X_1 + X_2 + X_3}{3}
\end{align*}
\]

3.2 The application of GWO

The steps of using GWO to solve the VPP optimization scheduling problem are as follows:

1) Initialize the parameters of the GWO algorithm: set the population number, iteration times, optimization problem dimension, and the search range of the \( \alpha \) wolf, and \( \delta \) wolf corresponding to the power generation units participating in the scheduling;

2) Take the economic benefit in VPP as the objective function, that is, the fitness value of the GWO algorithm, and update the position of the wolf according to the fitness value;

3) Surround the prey through Equations (16) and (17);

4) Update the position of the wolf \( \alpha \), \( \beta \) and \( \delta \) through equations (20)-(22), determine the position of the prey (the optimal solution), and iterate until the optimal solution that meets the conditions is found.

The process of GWO in solving the VPP optimization scheduling problem is shown in Fig. 1.
Start

Initialize GWO: Population size $N$, maximum iterations $t_{\text{max}}$, Search dimension $N$, Search bounds of $\alpha$, $\beta$, $\delta$

Initial iteration $t=0$

For $i=1:N$

Calculate objective function (fitness)

Update the value of $\alpha$, $\beta$, $\delta$

$t=t+1$

For $i=1:N$

Update the positions of $\alpha$, $\beta$, $\delta$, $\omega$

Calculate the best value of objective function

YES

$t\leq t_{\text{max}}$?

NO

End

Fig. 1. Flow chart of GWO algorithm.

4. Simulations and Discussion

4.1 Description of the case

The VPP is composed of wind power, photovoltaic, diesel generator and DR. It is divided into two sub-VPPs to manage in this VPP. And the parameters of VPPs are shown in Table 1. The prices of electricity market and VPP contract are listed in Table 2. The prediction data of Wind, PV and Load are shown in Fig. 2. And the weight coefficients $w_1=w_2=0.5$. Finally, the model is solved by the GWO algorithm.

Table 1. Parameters of VPPs.

| units | VPP1 | VPP2 |
|-------|------|------|
|       | DG1 | DG2 | Pg1 | DR1 | DR2 | DG3 | DG4 | Pg2 | DR3 | Ptr |
| Max/kW | 9  | 9  | 2   | 0   | 0   | 9   | 9   | 2   | 0   | 10  |
| Min/kW | 0  | 0  | -2  | -30 | -35 | 0   | 0   | -2  | -40 | -10 |
Table 2. Prices of electricity market and VPP contract.

| t/h | $\lambda_1$/t/h | $\lambda_2$/t/h | t/h | $\lambda_1$/t/h | $\lambda_2$/t/h |
|-----|-----------------|-----------------|-----|-----------------|-----------------|
| 1   | 1.57            | 1.2             | 13  | 7.30            | 6.5             |
| 2   | 1.40            | 1.0             | 14  | 7.80            | 6.5             |
| 3   | 2.20            | 1.5             | 15  | 8.50            | 7.5             |
| 4   | 3.76            | 3.0             | 16  | 7.10            | 6.4             |
| 5   | 4.50            | 4.0             | 17  | 6.80            | 6.0             |
| 6   | 4.70            | 4.2             | 18  | 6.30            | 5.5             |
| 7   | 5.04            | 4.6             | 19  | 5.80            | 5.0             |
| 8   | 5.35            | 4.5             | 20  | 4.20            | 3.8             |
| 9   | 6.70            | 6.0             | 21  | 3.80            | 3.0             |
| 10  | 6.16            | 5.8             | 22  | 3.01            | 2.5             |
| 11  | 6.38            | 5.7             | 23  | 2.53            | 2.0             |
| 12  | 6.82            | 6.0             | 24  | 1.42            | 1.1             |

Fig. 2. Prediction diagram of Wind, PV and Load.

4.2 Results and Analysis

The renewable energy resources (wind and solar) are at the highest priority, and can be all accepted by the VPP.

Fig. 3 shows the power output of all units in VPP1 in a day. Comparing it with Table 2 and Fig. 2, which can be seen that during the period from time 8 to 18, the DG power generations are greatly reduced due to the operation of the photovoltaic unit. And the electricity price during this period is relatively high. Thus, the amount of DR power reduction has increased.

Fig. 3. The power curves in VPP1

Fig. 4 shows the scheduling results of VPP2 in a day, and the power output trend is roughly the same as that of VPP1. Since the cost of DG power generations in VPP2 are lower than the cost of DG power generations in VPP1, DG contributes more in VPP2.
Fig. 4. The power curves in VPP2

Fig. 5 shows the interaction power between VPP1 and VPP2 in a day. It can be seen that VPP1 purchases a large amount of electricity from VPP2, thereby linking the sub-VPPs, taking the lowest overall VPP cost as the common goal, and complementing each other in power.

Finally, the power generation cost of VPP1 is $90.9624. And the cost of VPP2 is $-461.3215, which means that the system's electricity sales revenue is greater than the power generation cost, and the total system cost is $-370.3591.

5. Conclusion
The proposal of VPP reduces environmental pollution and improves the utilization rate of new energy effectively. In order to improve the efficiency of VPP management, this paper proposes a multi-VPPs optimal scheduling model based on the idea of distributed management. This model considers the power generation cost of VPP and the income of electricity purchase and sale from the interaction with the grid, and then takes the lowest VPP cost as the objective function, and takes into account multiple constraints such as climbing constraints, upper and lower limits, to achieve large-scale VPP sub-economic optimization Scheduling. Through the analysis of the case study, it can be known that the model can maximize the use of new energy. And through the power interaction between the sub-VPPs, the VPPs are connected to achieve the lowest cost of the system. Finally, the GWO algorithm is used to solve the VPP day-ahead optimization scheduling model. This algorithm simplifies the solving steps and improves the economic benefits of daily operation.

Acknowledgements
This work was supported by the Natural Science Basic Research Program of Shaanxi (No. 2020JM-542), the National Science Foundation of China (Grant No. U20B2029), the Science and Technology Basic Research Program of Shaanxi (No. 2021JM-404), and the Key Research Program of Shaanxi (No. 2021KW-33). And funded by Xi'an Shiyou University Graduate Student Innovation and Practice Ability Training Program.
References

[1] Z. Liang, Q. Alsafasfeh, T. Jin, H. Pourbabak, W. Su, Risk-Constrained Optimal Energy Management for Virtual Power Plants Considering Correlated Demand Response. IEEE Transactions on Smart Grid, 10, 1577-1587 (2019)

[2] W. Guan, L. Peng, J. Yang, et al, Multi-Objective Stochastic Scheduling Optimization Model for Virtual Power Plant Considering Uncertainty of Wind and Photovoltaic Power. Electric Power, 50, 107-113 (2017)

[3] Y. Wang, X. Ai, Z. Tan, L. Yan, S. Liu, Interactive Dispatch Modes and Bidding Strategy of Multiple Virtual Power Plants Based on Demand Response and Game Theory. IEEE Transactions on Smart Grid, 7, 510-519 (2016)

[4] N. Wenjuan, L. Yang, W. Beibei, Demand response based virtual power plant modeling considering uncertainty. Proceedings of the CSEE, 34, 3630-3637 (2014)

[5] W. Zhinong, Y. Shuang, S. Guoqiang, S. Yonghui, Y. Yang, W. Dan, Concept and Development of Virtual Power Plan. Automation of Electric Power Systems, 37, 1-9 (2013)

[6] R. Zhang and B. Hredzak, Distributed Dynamic Clustering Algorithm for Formation of Heterogeneous Virtual Power Plants Based on Power Requirements. IEEE Transactions on Smart Grid, 12, 192-204 (2021).

[7] L. Siyuan, A. Qian, Z. Jianping, W. Renbo, Bi-level Coordination Mechanism and Operation Strategy of Multi-time Scale Multiple Virtual Power Plants. Proceedings of the CSEE, 38, 753-761 (2018)

[8] C. Yu, W. Zhinong X. Zheng, H. Wenjin, S. Guoqiang, Z. Yizhou, Optimal Scheduling Strategy of Multiple Virtual Power Plants Under Electricity Market Reform. Automation of Electric Power Systems, 43, 42-49 (2019)

[9] D. Wenlue, W. Qun, Y. Li, A Coordinated Dispatching Model for a Distribution Utility and Virtual Power Plants with Wind/Photovoltaic/Hydro Generators. Automation of Electric Power Systems, 39, 75-81 (2015)

[10] Lyu, Xiaoyu, Zhiyu X., Ning W., Min F., and Weisheng X., A Two-Layer Interactive Mechanism for Peer-to-Peer Energy Trading Among Virtual Power Plants. Energies 12, 3628 (2019)

[11] Mirjalili S., Mirjalili S. M., Lewis A., Grey Wolf Optimizer. Advances in Engineering Software, 69, 46–61 (2014)

[12] Mohd H. S., Zuriani M., Mohd R. M., Omar A., Using the gray wolf optimizer for solving optimal reactive power dispatch problem. Applied Soft Computing, 32, 286-292 (2015)

[13] Arora S., Singh H., Sharma M., et al. A new hybrid algorithm based on grey wolf optimization and crow search algorithm for unconstrained function optimization and feature selection. IEEE Access, 7, 26343-26361 (2019)

[14] Raj S., Bhattacharyya B., Reactive power planning by opposition-based grey wolf optimization method. International Transactions on Electrical Energy Systems, 3, e2551 (2018)